Computers and Electronics in Agriculture 193 (2022) 106693

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

Image processing strategies for pig liveweight measurement: Updates and challenges

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ARTICLE INFO

Keywords:
Pig
Live weight
ANN
Image analysis
Body measurements

ABSTRACT

Liveweight (LW) of pigs is a key feature to monitor daily gain, nutritional status, and health performances and to forecast and control their marketable weight. The direct method of measurement is the most prevalent system which involves weighing of the pigs on a scale which can be a strenuous process for both the animal and the stockman. The non-contact method for LW estimation uses measurements of physical dimensions of the animal and then correlating them to the animal's LW to minimize any stress. The advent of non-contact image based techniques, computer vision systems (CVS) and artificial intelligence (AI) has led to employment of such advancements for LW estimations in pig and in other species. The pork processing industry lags in planning procurement strategies due to the difficulties in pig growth estimation. Machine learning (ML) tools can be effectively applied to recognise such issues. However, the precision level of automated techniques for pig weighing may suffer constraints because of pig movements, low ceiling heights and low illumination intensity in the farm that restrict proper imaging. After image acquisition, images undergo several processing steps including pre-processing, filtering, feature extraction, training and database formation for reliable forecasting of LW. ANNs and CNNs in conjugation with image processing can be successfully used as an alternative to multiple linear regression analysis with improved accuracy of prediction. This review tends to highlight significant advances that have been made for CV + ML based pig weight measurement and the areas in which further research is still desired for complete automation in farm situations.

1. Background

Pig farming makes a direct contribution to livelihood of millions of people globally. Traditionally, pigs are raised in conventional small-scale production systems with low labor input. Health is a crucial element in pig welfare, and daily weight gain is an appreciated indicator of sound health and production (Benjamin and Yik, 2019). Liveweight (LW) of pig is the key feature to monitor daily gain, nutritional status, and health performance, and to forecast and control their market weight (Menesatti et al., 2014). Individual weight measurement is considered as an important practice to be followed in swine farm management. Effective management of pigs is a critical tool for quality pork production and, the ability to assess pig weight accurately before setting up the harvesting goals for slaughter is very significant in economic pig farming (Stygar and Kristensen, 2016). Precision in predicting pig weight reduces the feed costs which otherwise accounts for 60% of the total production cost and can enhance profitability in commercial farms (Sungirai et al., 2014). Besides predicting market weight for slaughter, accurate antibiotic dosing and improved feed formulation are other appreciable benefits of accurate LW estimation in pigs.

Conventionally, pig weight is measured using a weighing scale only at the beginning and end of a production cycle, often only for a small subsection of animals, and not for every animal in the herd (Schofield, 1990). The growing demand for pork and other by-products has enforced an intensive system of pig rearing. To upkeep with the rising market demands along with providing satisfactory care to the individual animals of the farm, it is recommended to engage in automated systems to improve management, health status, animal welfare and productivity (Morris et al., 2012). In such scenarios, a modern day application can be explored to approximate the weight of pigs using two dimensional (2D) images which can prove very useful and time efficient in many industries and also in daily farm activities (Chaithanya and Priya, 2015). It aids the farmer to run a profitable venture by identifying slow-growers in the herd and take appropriate decisions. Therefore, this review focuses on the recent applications of image processing for pig liveweight estimation.

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https://doi.org/10.1016/j.compag.2022.106693
Received 23 September 2021; Received in revised form 3 January 2022; Accepted 6 January 2022
Available online 11 January 2022

2. Strategies for pig liveweight measurement

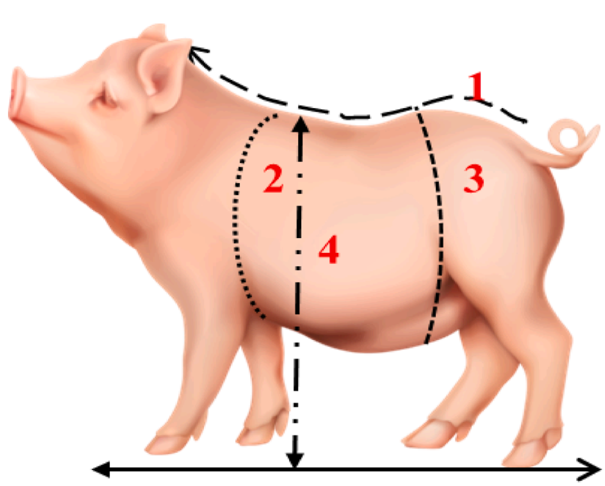
The LW of pig can be determined through various methods. Most assessments of pig conformations are eye and hand observations based on the experience of the observer (Wu et al., 2004). Broadly, there is a direct approach and an indirect approach to determine the LW of pigs.

2.1. Direct weighing of pig on ground scale

The direct method is the most prevalent system which involves direct weighing of pigs by manually moving them to the weighing location and retaining/restraining them on a weighing scale to record observations (Lee et al., 2016; Pezzuolo et al., 2017). However, this approach is labor dependent and challenging which leads to deleterious effects such as stress, weight loss and even injury to the stockman or to the animal, occasionally resulting in animal loss (Grandin and Shivley, 2015; Faucitano and Goumon, 2018). Generally, two farmworkers get engaged spending 3–5 min on weighing of each pig on a weighing scale (Brandl and Jørgensen, 1996). Continuous physical interaction of the weighing machine with the animal may give faulty results due to technical error. Although the most accurate LW output is generally expected by direct weighing but it is a cumbersome and time consuming process (Al Ard Khanji et al., 2018; Wang et al., 2021).

2.2. Morphometric measurements for pig liveweight assessment

There are other well proven methods for LW estimation that encompasses measurements of physical characteristics of the animal and then correlating them to the animal's LW to minimize any detrimental stress. The heart girths (HG), body length (BL), wither height (WH) and flank measurements (Fig. 1) are the main parameters used in weight estimation (Banik et al., 2012). BL is defined as the length from the base of the neck to the base of the tail, whereas the HG is the chest area behind the forelegs (Sungirai et al., 2014). Girth measurement is also considered of prime importance in the indirect assessment of pig's LW (Pope and Moore, 2002). Panda et al. (2021) reported that BL, heart girth, paunch girth, WH, height at back, rump width, thigh circumference, neck circumference, and body depth had high correlation coefficients (0.8–0.97) with LW. Also, body length and HG were analysed to be best fitted for prediction of BW with high R^2 values. Machebe and Ezekwe, (2010) also reported high correlation of BL and HG with pig body weight in their study. About 98% of the variation between BL and LW in pigs was attributed to BL while HG explained 89% of the variation between BL and LW. Banik et al. (2012) witnessed that the variation in LW was highly attributed to height at fore leg (20.98%), BL (19.50%), HG (6.60%) and paunch girth (5.80%) in defining pre-weaning LW in Ghungroo pigs. Body parameters such as BL and HG were also found effective in successful assessment of LW (Mutua et al., 2011; Alenyoregue et al., 2013; Sungirai et al., 2014 and in Walugembe et al., 2014). A prediction model was prepared by Oluwole et al. (2014) taking body height, HG, BL, snout length and rump circumference in consideration for LW prediction. In another study, Al Ard Khanji et al., (2018) observed that BL, HG and flank-to-flank distance were helpful in assessing LW in pigs. Table 1 provides an overview of the prediction efficiency of multi-linear regression models for different breeds of pigs. Although this approach is relatively simple and cost effective, it can be inconvenient for large scale commercial farmers to practice such a system for predicting the LW. Indirect/non-contact methods of weight estimation are therefore needed to make the weighing process more convenient.



1= Body length, 2= Heart girth, 3= Paunch girth, 4= height at withers

Fig. 1. Body measurements terminologies of pig.

2.3. Indirect approach to estimate pig liveweight

Visual estimation of weight using linear body measurements and image analysis is gaining popularity (Zaragoza, 2009). Numerous potential applications of digital image analysis in livestock activities were identified in the previous years. Out of these, pig LW estimation was recognised as the primary application of image analysis in livestock production (Li et al., 2013). Machine vision-based weighing of pigs is a non-intrusive, fast and accurate approach that reduces stress for both the animal and the handler (Wang et al., 2008). Automated monitoring of animals based on image analysis is a novel approach, which has been proven beneficial to farm managers in various studies (Aydin et al., 2010; Poursaberi et al., 2010). Visual image analysis (VIA) is an emerging technique for continuous real-time monitoring of pig weight gain and aiding in earlier diagnosis of issues in the herd allowing appropriate management decisions to be taken in a timely manner. The VIA method uses images of pigs captured in real-time to define the body surface dimensions to determine LW and identify the loopholes in current farm practices impeding to attain required market size.

Camera-based monitoring devices have emerged as a promising concept in precise livestock farming because of different applications and non-contact mode of retrieving data from animals (Salau et al., 2021). However, in dairy science, considerable number of camera-based studies have been successfully conducted like lameness detection in cattle (Van Nuffel et al., 2015; Zhao et al., 2018); determination of body condition (Halachmi and Guarino, 2016); and energy reserves of cattle (Alvarez et al., 2019). The extended use of cameras was also noticed in

Table 1
MLR models using morphometric measurements for LW estimation of pigs.

Model	Breed/Strain	R^2	Reference
MLR	–	0.97 (BL), 0.98 (HG)	Machebe and Ezekwe (2010)
MLR	Kenya pigs	–	Mutua et al. (2011)
MLR	Large white Yorkshire	0.93	Alenyoregue et al. (2013)
MLR	Rattlerow seghers × Pietrain Plus	0.871	Kashiha et al. (2014)
MLR	Landrace, Large white Yorkshire	0.87	Sungirai et al. (2014)
MLR	Ugandan village pigs	0.89	Walugembe et al. (2014)
MLR	Nigerian pigs	0.86	Oluwole et al. (2014)
MLR	Crossbred pigs	0.91	Al Ard Khanji et al. (2018)
MLR	–	0.835 (BL and HG)	Kaewtapee et al. (2019)

*MLR = Multi-linear regression, MAE = Mean absolute error, BL = Body length, HG = Heart girth.

animal identification (Thomasen et al., 2018), animal behavior (Salau et al., 2018) and the monitoring of herd activities (Guzhva et al., 2016). In addition, the use of advanced non-contact sensing technologies such as the Light Detection and Ranging (LiDAR) sensor for estimating body size measurements in cattle based on three-dimensional reconstruction models have gained significant attention due to high accuracy (2 mm) and 2% error margin (Huang et al., 2018). In a similar investigation on LW estimation of pigs using body measurement, Pezzuolo et al. (2018a) implemented a Structure from Motion (SfM) photogrammetry for 3D reconstruction of the pig body enabling 80% characterization of the total animal area.

From the discussions made so far, it can be stated that the experimental frameworks for image acquisition and processing used for pig weighing may give imprecise results because of pig movements, low ceiling heights and low light intensity in the farm for proper installation of a camera (Buayai et al., 2019). Therefore, it is imperative to optimize such imaging conditions for estimating LW with higher accuracy. This section discusses some of the imaging framework design considerations that have been investigated till date.

2.3.1. *Animal stance during imaging*

Most of the digital image-based methods for estimating a pig's LW requires the pigs to be in an appropriate position and quite stationary. To accomplish higher accuracy in weight estimation, either stationary stance of animal or use of more than 2 synchronized cameras are required (Rahagiyanto and Adhyatma, 2021). This condition is not feasible on a farm because it is hard to keep the animal stationary and restrain it in a certain desired position for a long time. In seals (De Bruyn et al., 2009) and sea lions (Waite et al., 2007) animal immobilization was achieved by anaesthesia to estimate the LW. However, it does not appear to be an appropriate solution because of the cost involved and certain limitations of taking measurements on lying animals. Thus, a 2D imaging approach using synchronized cameras in animal's natural moving condition were developed to measure the body parameters. VIA systems can accurately estimate LW with the data available on correlating body area and LW. Related studies indicated that the standing position, body alignment and head of pigs influenced the machine vision and performance of image analysis in weight estimation (Wang et al., 2008; Wongsriworaphon et al., 2012, 2015; Kashiha et al., 2014). The non-straight postures of pigs during image capture were also reported to affect the image pixels, resulting in less accurate models for weight estimation (Jun et al., 2018). Thus a need was felt to design a frame or an image capture system to overcome such practical issues.

2.3.2. *Camera position*

Since 1991, imaging with a top-view camera has been known as the least distressing technique for animals to generate relevant data in a sophisticated manner to implement algorithms in realistic situations (Van der Stuyft et al., 1991). Past researches have indicated that the top view area of the pig, minus the head and neck is highly correlated to LW. Few other researchers also suggested that LW and top-view body area have a linear relationship that can be expressed as a linear regression equation capable of predicting the LW of animals (Schofield et al., 1999; White et al., 2004). In this context, image processing technology can prove worthy in determining the body area by aerial view of a pig's body in contemporary farming. Pigs are generally imaged from the top angle and seldom imaged from sides. Wang et al. (2008), imaged few pigs predominantly from the top but from the sides as well and later processed them by a computer to correlate the optimum features. Pig LW was predicted using ANN technique and compared with the morphometric mass and the actual weight with a R^2 value of 0.993 and 0.992 respectively with error of 3%.

2.3.3. *Illumination intensity during imaging*

Good quality imaging needs proper lighting distance, wavelength, and applied filters (Pezzuolo et al., 2018b) along with a contrasting background (Wurtz et al., 2019). Even after extensive research and advancements, imaging techniques still have some limitations. Its complete implementation in the real farm environment suffers with certain restrictions as the stalls are susceptible with uneven and inconsistent lighting. The data extracted from images taken in different environmental situations may interfere in image processing and analysis leading to erroneous results (Yang and Xiao, 2020). To make a precise forecast, the straight posture of pigs along with illumination stability and minimal human intervention has been considered to be of vital importance (Jun et al., 2018). Illumination is also an important factor for determining the accuracy of the image processing output. Schofield et al. (1999) captured good quality pig images in added low-level illumination setups in the feeding area. Although, image capturing is beneficial in outdoor pen for pigs as well as farm workers but illumination is inconsistent in such locations. The varying brightness during the day because of indirect sunlight may pose challenges for image processing. Even for the Kinect images, infrared from sunlight may influence the continuously emitted infrared dot patterns, thus interfering with the measurements. Jun et al. (2018) conducted an investigation with the objective to develop a non-stressful method considering free moving animal postures using only 2D features. In this work, sunlight was believed to distort the depth and thus the depth information was ignored. The mean absolute error (MAE) of 3.15 kg and $R^2 = 0.79$ was achieved. Such large variation was due to sunlight intrusion resulting in incorrect pig image segmentation. Kashiha et al. (2014) suggested that illumination is important in identification and segmentation of the images but an overtly bright illumination can cause faulty identification as the contrast of the dark paint patterns can decrease against a bright skin pig. In their study, a walk-through computer vision-based system for pig weighing was developed comprising a video camera and a computer for image acquisition, image processing, feature extraction and data analysis. The light period of pigs was controlled by a 12 h light period timer from 07:00 h to 19:00 h with a minimum of 40 lx and a maximum of 176.1 lx light intensity. Buayai et al. (2019) captured gray scale images in a low-light environment with light density <0.01 lx and infrared light on, whereas color images were captured in an uneven lighting environment with light density of ≥ 0.01 lx with infrared lights off. The image segmentation technique is sensitive to the light intensity and works well in a controllable environment with a dark-colored background. As the illumination level in animal pens is quite low, poor-quality image segmentation was obtained that could not to be processed further (Wongsriworaphon et al., 2015). Pezzuolo et al. (2018c) captured pig images in an average light intensity of 70 lx measured at ground level using a luminance meter with a 12 h light- dark cycle.

Low light intensity can make the segmentation process even more difficult against dark backgrounds. The black background has a great contrasting effect on whitish color pigs. A white background against blackish breeds and black or white background or other colors for breeds with a grey color can be chosen (Wang et al., 2008). These light differences and the background conditions makes practical application of cameras with their image segmentation algorithms difficult. The algorithms developed by Kashiha et al. (2014) were found optimum only for white animals on a dark floor and are not suitable for implementation in commercial farms with different backgrounds, illumination conditions, and animal coat colors. At the same time, the depth images remain unaffected with background colors and suffer only from extreme light conditions that increase the noise at the pixel level.

2.3.4. *Optimum imaging conditions for constraint minimization*

In order to minimize the effect of the earlier discussed constraints, Wang et al. (2008) designed a walk-through image capture system to work well without interfering with the pig movements during imaging. Appropriate features were extracted using ANN to achieve higher accuracy in predicting the pig LW. The pigs were guided to walk from one pen to another through a 1 m wide passage with a top view camera fixed on the ceiling at a distance of 2.21 m between the camera lens and the ground with a frame rate of 15 frames per second (fps). Two 40 W white fluorescent lights were arranged at a height of about 1 m above the ground level on each side of the passage, to provide stable illumination during the trials. In another study, images of cattle, already acclimatized to pass through the walkway in an unconstrained manner were captured through 3D Kinect-like depth camera mounted 2.3 m above the ground and aligned with a computer system focusing on the back of the animal from above to capture better images with full field view in the least stressful manner (Hansen et al., 2018). In a similar pattern, Salau et al. (2021) recorded images of Holstein Friesian (HF) cows while passing freely through a framework of 2 m high and 2 m wide passage. To capture both the sides of the cows simultaneously, three depth cameras were installed diagonally on each side of the framework. Additionally, two side view Kinect cameras at a height of 0.6 m above the ground were also installed with optical axis parallel to the ground and directed inwards.

In a trial, Jun et al. (2018) captured 2D images of pigs kept free in a spacious pen with the help of an overhead infrared based depth camera in a stationary position overseeing the centre of the pen allowing only one pig at a time. Thus, various postures of pigs with relatively straight or twisted body shapes and different head positions and orientations were captured. According to Wang et al. (2008), Wongsriworaphon et al. (2012, 2015), and Kashiha et al. (2014), the pigs' feeding posture generates superior pig weight estimates by image analysis and machine vision. Based on this information, Buayai et al. (2019) fixed the imaging systems over the feeder area in the pen. Two cameras were installed at the top right and top left of a wheel feeder at a height of 2.0 m from the floor to the ceiling. The distance of the camera lens from the floor was adjusted to 1.84 m allowing up to six pigs to enter the feeder at the same time with a goal to develop a cost-effective and applicable machine vision-based pig weighing system with minimal botheration to the pigs. Pezzuolo et al. (2018c) also fitted two Kinect cameras in the feeding area of each pen of 6.75 m × 3.10 m size allowing lateral and top imaging of the pigs' body to estimate LW of crossbred pigs in farms of Italy installed Kinect depth camera combined with an infrared laser emission source to reconstruct 3D image with an infrared-sensitive camera suspended by aluminium rods at a height of 3 m above each water crate which were already installed with auto-weight measuring scale. To optimize the working distance, depth cameras were positioned with adjustment capabilities and a frame rate of (>10 Hz). The cameras were alternatively turned on and off and captured 20 fps with 57° horizontal × 43° vertical angular field of view with 60 potential extracted variables for further analysis. Image acquisition was done by Software Development Kit (SDK v.7.1). Wongsriworaphon et al. (2015) collected a dataset of 456 good-quality images of whitish crossbred B91 pigs (Largewhite, Lancerace and Duroc) while standing in a custom-made rectangular setup area of 90 × 160 m^2 with a digital camera of 640 × 480 pixel resolution. The camera was mounted in a fixed position which was 2.8 m above the farm floor to capture good quality pig images.

2.3.5. Advantages and limitations of different imaging approaches

Although 2D imaging technique provides digital information to estimate pig growth rates within an accuracy of 1 kg (Deboer et al., 2013), it requires sufficient illumination and contrasting background, for instance a white pig on a dark background. The other major drawbacks of 2D imaging technique constitute less morphometric measurement sites and a long processing time as the field view of the camera is unable to reach the desired site. To compensate for such inadequacies, 3D imaging techniques were established where the measurements can be carried out by more than two cameras inter-connected to each other with the help of predefined angles. In 2D image analysis, the accuracy of both image and measurements based results are dependent on resolution, the precision in measurement of distance between animal and camera, and the orientation if the animal with respect to the camera. One of the prerequisites of 2D image capture is that the morphometric variables should remain perpendicular to the optical axis while, perfect perpendicular orientation of the camera to morphometric variables is not essential in 3D imaging. Hence, more liberty is experienced in imaging animal from different viewpoints in a 3D imaging setup (Putra et al., 2016). The 3D depth-based sensor cameras such as Microsoft Kinect (Microsoft, Redmond, Washington) and Intel® RealSense™ (Intel, Portland, Oregon) are fitted with a high-definition system, an infrared illuminator and time-of flight (ToF) depth sensor to produce color. Further in comparison to ANN, Convolutional neural networks (CNN) are complex analogues with an excellent performance in image analysis data. CNN encodes image-specific features into the model, making it more applicable for image based tasks while further reducing the parameters required for setting up the model. CNN uses spatial information between the pixels of an image while ANN struggles with the computational complexity of image derived data. CNN comprises of multiple layers including the convolutional layer, non-linear layer, pooling layer and fully-connected layer. It uses kernels, where each node associates a kernel with the input image and produces the convolved image as output. Image scales in CNN can also be changed using strides to create smaller output images than the input, or transpose the convolutions to create an output image larger than the input. Pooling and upsampling layers also aggregate the input image values into smaller images, or interpose smaller images' values into bigger images (Oliveira et al., 2021).

3. Image processing strategies

After image acquisition, images undergo a lot of processing steps before the application of modelling tools to predict the weight of the animal. The overall process steps can be classified as: 1) acquiring an image, 2) pre-processing 3) filtering the image 4) feature extraction 5) model training and, 6) saving the pattern to knowledge base for reliable forecasting of LW (Fig. 2). According to Dalai and Senapati (2017), the shape, boundary, height, length, and color are various attributes that can be retrieved from the captured images using various image processing and segmentation techniques. Two perpendicular views can be best utilized to derive the volume of each item, which can be used to predict the weight of the object with 90% accuracy.

3.1. Object detection

This operation is performed to determine whether the object captured in the camera's field of view is of analytical interest or not (a pig in this case). If in case such an object is detected, it is then isolated from the background (or segmented) and separately studied (Kollis et al., 2007). Generally, it is assumed that a camera placed on top in a farm will capture frames of only the desired object with the largest area characterizing the animal. Advanced options such as automatic detection through ML, and DL approaches (Zhang et al., 2018) or radio-frequency identification devices (RFID) and CVS fusion (Velez et al., 2013) apart from the traditional approach to mark pigs using dyes, paints and detect the colors in the image, are used (Yao et al., 2019). The most effective object detection algorithm is the deep learning algorithm (LeCun et al., 2015). Object detectors in recent practice are based on faster R-CNN (Region-based convolutional neural networks), R-FCN (Region-based fully convolutional network, SSD (Single shot detector), YOLO (You only look once) and Multibox (Huang et al., 2017). Cang et al. (2019) employed faster R-CNN network along with a regressive branch activated by ReLU (Rectified linear unit) activation function and observed that the strategy performs pig recognition, location detection and pig weight estimation simultaneously with an MAE of 0.644 kg and relative error of 0.374%. Most methods binarize an image into black and white pixels, eliminate small size pixels, and then try to fit ellipses around white pixels which has received accuracy up to 88.7% (Kashiha et al., 2013) and 95.8% (Nasirahmadi et al., 2015). 2D and thermal images are restricted to analyse body contour and cross-sectional data whereas 3D images study depth information on the body surface of the

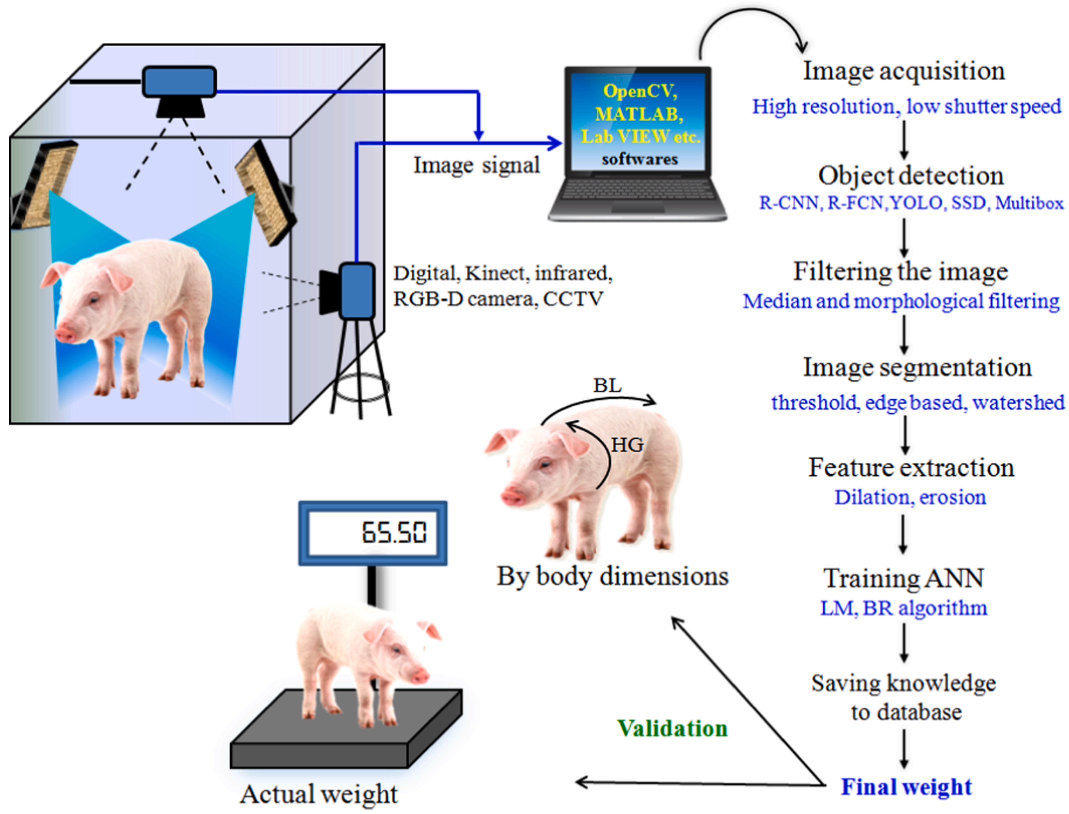


Fig. 2. Basic image processing steps for predicting pig liveweight.

object. Tu et al. (2021) adopted R-CNN algorithm with soft non-maximum suppression (soft-NMS) and traditional NMS to perform detection using python 3.6 on 290 training and 130 test images of pig. Back-propagation and stochastic gradient descent (SGD) were used to train the 3 phase R-CNN model with a precision level of 94.11%.

3.2. Filtering of image

Filtering is performed on a segmented image in order to remove spurious segmented pixels and to fill in poorly segmented regions of the target object. The segmentation process will separate most of the pig pixels, but there can still be numerous pig image pixels which remain undetected. Further, any number of background pixels may have intensity above the set threshold for their removal and thus be falsely segmented. It is therefore essential to perform filtering diligently to clean up the segmented image (Kollis et al., 2007). There are two forms of filtering; median filtering and morphological filtering. In a binary image, the median filter replaces each pixel with the value (1 or 0) which is in the majority neighbourhood of that pixel. It is able to correctly isolate segmentation errors without causing great distortion to the image. The morphological filtering corrects an image with each pixel value indicating the contrast intensity in the neighbourhood of that pixel.

3.3. Image segmentation

The aim of segmentation is to segregate the object of interest from the rest of the image. The segmentation process is a three step process: firstly, to identify pig in the image; secondly, to segment the pig's body in the image and, lastly, feature extraction. The image segmentation technique that is mainly applied in image analysis is watershed segmentation algorithm (Chaturvedi et al., 2012) apart from the fixed threshold segmentation. In a study, Kashiha et al. (2014) reported that the captured video images were processed in MATLAB v.2010A to extract the outline of the body area, and segmentation of pigs in the image was carried out with an ellipse fitting algorithm with thehead and neck separated from the body to maximize correlation to LW. In another related study, the acquired images were managed in MATLAB v.2013 creating a loop of 50 frames per acquisition. Manual image selection was performed to ensure better results which were further analysed with the image processing toolbox to eliminate the floor background and remove head, ears and tail of the pig (Kongsro et al., 2014). This helped to improve accuracy and to eliminate tiny background interference. Later, an algorithm using the sum of pixel values from segmented pig images was developed in MATLAB to measure the volume of pigs and was further used to form a statistical relationship with the recorded weight.

$$v = sum(X)$$

$$V = sum(v)$$

where, v is a row vector with the sum over each column of the image matrix X and V is a scalar of the sum of the row vector and v representing the volume measurement of the pig.

Suwannakhun and Daungmala (2018) in their study cut off the background in the pig image using the threshold (thr) method. Subsequently, the value of each pixel was compared to the threshold. If f (x, y) $<$ threshold, the pixel is black or fractional while in case of f (x, y) $\geq$ threshold, the pixels are either white or part of the background.

$$f_{thr}(\mathrm{x},\mathrm{y}) = \begin{cases} 1, f_f, x, y < threshold \\ 0, f_f, x, y \geq threshold \end{cases}$$

where, 1 = black part of the object. 0 = white, which is part of the background.

Feature selection from the images can be a cumbersome task because of large number of morphometric measurements, thus CV + ML approach can be applied for automation of feature selection with higher efficiency (Tasdemir and Ozkan, 2019; Gjergji et al., 2020; Rudenko, 2020). CV and CV + ML approach both count for manual intervention up to some extent in image and feature selection, image segmentation, and morphometric measurement extractions. However, CV + deep learning (DL) approach states for full automation of the LW prediction processes resulting in substantial improvements in LW prediction as compared to other traditional practices (Fernandes et al., 2019; Gjergji et al., 2020). Hu et al. (2021) used a new approach for pig instance segmentation with two types of attention blocks into the feature pyramid network (FPN), which encoded a channel attention block (CAB) and a spatial attention block (SAB), respectively to remove the constrains of sundries barrier and overlapping. CAB highlights the interdependencies within the channels and the SAB sums up the weighted sum of the features at each position. A dual attention block (DAB) was proposed to integrate CAB features with SAB information flexibly.

3.4. Feature extraction

There are two major approaches for feature extraction: (1) using the body dimensions of pigs such as maximum width of rear section, minimum width of front section, tail to scapula length and the rear area (Banhazi et al., 2011; Li et al., 2015); (2) using pig boundaries such as enclosed area, perimeter, eccentricity, minor axis length, and major axis length (Wang et al., 2008; Kashiha et al., 2014; Kongsro, 2014; Wongsriworaphon et al., 2015). Feature extraction by using the boundary characteristics is more dynamic than using body measurements in pig. Buayai et al. (2019) used the automatic pre-selection method and manual selection for boundary detection, and selected the body area without the head and neck in the acquired image to achieve accurate pig weight estimates. Thus, common features like area, convex hull area, major axis length and minor axis length, equivalent diameter, perimeter, and bounding box area were extracted using the boundary characteristics of the pig image. Wang et al. (2008) after successful acquisition of pig images conducted automatic selection of images either by computer codes or manually by visual inspection. The selected images were analysed with MATLAB image processing toolbox and the feature extraction was done to eliminate the background interferences along with head, feet, ear and tail using the functions of image erosion and image dilation. Pig image parameters such as area, convex area, perimeter, eccentricity, major axis length and minor axis length were extracted.

The dataset of extracted image features and measured LWs can be manipulated for statistical analysis via custom codes. The CVS applied for image processing in the research by Fernandes et al. (2019) refers to the use of MATLAB v.2017b for the task. Suwannakhun and Daungmala (2018) in their study, used a dilation (enlarges the objects with increase in number of pixels in the image) and an erosion (shrinks objects and the number of pixels decreases in the image) for removing undetected pig pixels or pixels other than the pig after using threshold algorithm and for eliminating few background pixels which may be falsely segmented because of intensity higher than threshold. The dilation and erosion functionas can be mathematically expressed as:

$$\text{Dilation}: (A \oplus B)(x) = \{x \in X, x = a + b : a \in A, b \in B\}$$

$$\text{Erosion}: (A \Theta B)(x) = \{x \in X, x + b \in A : b \in B\}$$

Pezzuolo et al. (2018c) extracted and quantified different body-related parameters and analysed the depth images with the SPIP™, Image Metrology Inc. software. Each 3D image was processed to extract the pig contour to get relevant coordinates and positions of body parts; the body cross section was extracted and the body length, front height, back height and HG like body parameters were estimated to predict accurate LW. In another trial, Shi et al. (2016) acquired pig images using LabVIEW (Laboratory virtual instrumentation engineering workbench) with the VDM (vision development module) image acquisition system and further analysed the images on the machine vision module of the LabVIEW. The depth image was analysed by block matching method and the depth threshold technique was employed to remove the background instead of traditional gray threshold segmentation for a clear pig body contour and precise pixel values of the image.

3.5. Machine learning for pig liveweight prediction

Machine learning applications have been proven to be very useful and time saving to analyse the images of the object and increase the accuracy of forecast in daily life. The camera calibrations can be done using Open Source Computer Vision Library (OpenCV), a python open-source CV and machine learning (ML) software library developed by Bradski (2000). Open CV uses computer vision in artificial intelligence (AI), ML, image processing, video capture and analysis including features such as face detection and object detection for real-time operations. The most popular technique of camera calibration is the chessboard technique given by Zhang (2000). A 2D chessboard of known size is prepared and the angle of the chessboard is adjusted relative to the camera so that a group of chessboard images can be obtained by a camera (Luo et al., 2021). This helps to overcome the obscurity of lens distortion and non-normal image projective imaging.

AI implementation necessitates ML which is a subdomain of AI. MLs' basic aim is to feed the machine data from previous interactions as well as mathematical data to accomplish the allotted task of solving a specific problem (Kumar and Pillai, 2021). In the past few years, there has been a constant upsurge of interest in ML techniques and neural network modelling in various fields of science and arts. The first concept of artificial neural network (ANN) as an effort to model the neural activity of human nervous system was introduced in 1943 by Warren McCulloch and Walter Pitts (Salau et al., 2021). The main application of ANN is in forecasting or prediction of future behavior or unseen information from past examples. ANN is based on the neural structure of human brain, which processes information by means of interaction among many neurons. In simpler words, ANNs have greater flexibility than the traditional statistical methods as ANNs are appropriate for problems with no specified information available but have enough data in a generalized form. Thus, they can be treated as multivariate nonlinear models with extraordinary pattern recognition ability (Tarafdar et al., 2020). ANNs are capable of generalizing and inferring the hidden part of the information correctly from past behavior even if it has noisy information. It is a universal functional approximator as it approaches any continuous function with higher grades of accuracy. However, the other non-linear forecasting models have certain limitations with relationship between input and output variables that has to be hypothesized before predicting a phenomenon. ANN has been successfully applied in studying numerous complex phenomena of animal sciences, such as for predicting 305-day milk yield in Brown Swiss cattle (Gorgulu, 2012); breeding values for dairy cattle (Shahinfar et al., 2012); breeding values of milk production trait in Holstein cows of Iran (Hamidi et al., 2017); body part determination in HF cows (Salau and Krieter, 2020); culling reasons in HF cows on the basis of first-lactation performance (Adamczyk et al., 2021); milk yield curve in subsequent lactation period using deep learning in dairy cows (Liseune et al., 2021) etc. ANN models have a peculiar ability to learn from observed data requiring little or no prior knowledge of the task to be performed much effectively than the standard empirical models for characterization of complex systems (Afrand et al., 2016).

The pork processing industry lags in planning procurement strategies due to the difficulties in pig growth estimation. From the literature available, it can be stated that, ANN models can be effectively applied to recognize such issues (Barreto and Araujo, 2004). In recent studies, ANN models were applied to ease the estimation of individual pig weight as well as mean weight of pigs in the herd. The most popular type of ANN model is the multilayer feed forward network (Fig. 3), which involves an input layer; one or more hidden layers; and an output layer which altogether form a parallel and highly interconnected network (Ozdogan, 2021). The data at first is fed to the input layer and later transferred to

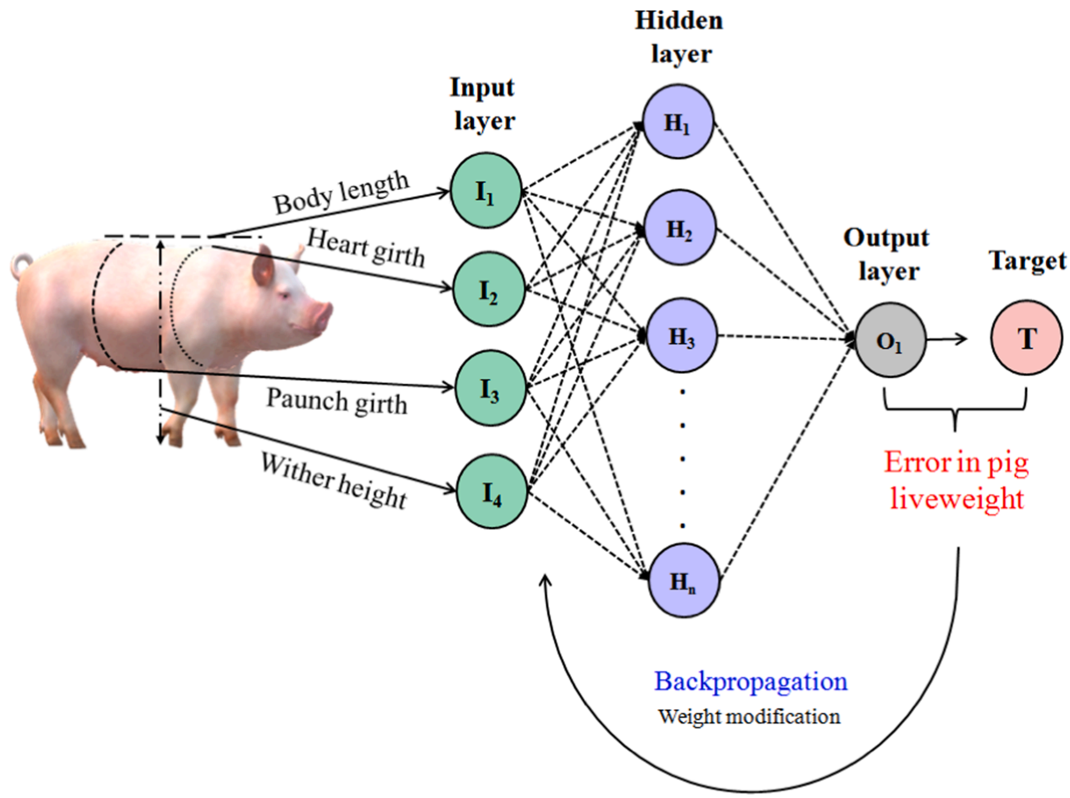


Fig. 3. Representative ANN infrastructure for pig liveweight estimation.

the hidden layers to give an output. Consequently, the output of the hidden layer serves as input for the output layer (Fernández et al., 2007, Celik, 2021).

Each layer comprises of numerous neurons interconnected to neurons of adjacent layer with some weights known as synaptic weights. These synaptic weights indicate the information used by ANN to establish data interactions (Baliyan et al., 2015). Back propagation (BP) algorithm is generally paired with multilayer feed forward ANN models for best performance. The BP neural network (BPNN), also referred to as the multilayer perceptron, is the most all purpose and commonly used neural network (Amraei et al., 2016). Table 3 illustrates the other widely used algorithm in this domain. For both cattle and pig, the least used modelling algorithm is the TFSISO (single input single output) and fuzzy logic. The application of deep learning algorithms in estimating LW of cattle and pigs is still limited (Dohmen et al., 2021) and requires more detailed investigations.

To predict broiler LW, Amraei et al. (2016) used five features: area, perimeter, convex area, major axis length and minor axis length, to train the ANN using Levenberg–Marquardt (LM) and the Bayesian regulation (BR) algorithm. The BR algorithm performed best with root mean square error (RMSE) of 82.30 for the total data set. In another study, Kashiha et al. (2014) designed a transfer function (TF) with the Captain toolbox in MATLAB considering body area as input and LW as output. The accuracy for the TF model was 0.962 for individual, and 0.975 for group weight estimation in pig. The results with TF model were compared with linear regression models (Schofield et al., 1999) and mixed effects (nonlinear) models (Schinkel et al., 2009).

Buayai et al. (2019) estimated pig weight utilizing multi-layer perceptron (MLP) network paired with BP technique and further exploited LM algorithm as it is the fastest algorithm for moderate size networks with minimum error (Moghadassi and Parvizian, 2009; Heidari et al., 2016). After processing the images, for a group of 39 pigs, Wang et al. (2008) used the length of major and minor axis, extracted area, convex area, perimeter and eccentricity as six input layer neurons, one hidden layer of BP algorithm with adjustable neurons and one neuron output layer (i.e. the mass of the pig). The output was compared with the morphometric mass and ground scale mass with a R^2 of 0.9932 and 0.9925, respectively as shown in Table 2.

In a similar research, the association between the extracted features and the LW was defined by Wongsriworaphon et al. (2015) using three learning algorithms: (1) the standard VQTAM (vector-quantized temporal associative memory), (2) the AR-based VQTAM, and (3) the LLE (locally linear embedding)-based VQTAM. The results showed that the combined algorithm of VQTAM and LLE algorithm was most accurate than others with only 2.94% deviation from the actual weights. In a study pertaining to broilers, Benicio et al. (2021) predicted weights of 80

Table 2
Machine learning models using image analysis for liveweight estimation of pigs.

ML Model	2D/3D	R^2	Error	References
BP	2D	0.992	3%	Wang et al. (2008)
ANN	2D	–	<3%	Wongsriworaphon et al. (2015)
Linear model	3D	0.993	1.75 kg	Shi et al. (2016)
MLP	3D/ CCTV	0.840	2.84%	Buayai et al. (2019)
ANN	2D	0.790	3.15 kg	Jun et al. (2018)
TF model	3D	0.954	1.33	Pezzuolo et al. (2018c)
MLP	3D	0.86	2.69	Fernandes et al. (2020)
Linear mixed model	3D	0.72–0.98 (1 day) 10.65–0.95(2 day) 0.51–0.94 (3 day) 0.49–0.93 (4 day)	–	Yu et al. (2021)

*ML- Machine learning, R^2 = Coefficient of determination, MLP = Multi-layer perceptron, TF = Transfer function model.

Table 3
Different algorithms used in pig image analysis.

Algorithm	Utility	Advantages	Limitations	References
Canny edge detection algorithm	Feature detection	Accurately detect edges in the images	Bias towards horizontal and vertical edges.	Rana (2020)
Watershed segmentation algorithm	Image segmentation	Fast, provides closed contours for complete division	Sensitive to noise and over segmentation	Chaturvedi et al. (2012), Dalai and Senapati (2017), Ju et al. (2018)
K-means clustering algorithm	Object detection	Centroid –based, groups the similar property unlabelled dataset into clusters	Cannot handle noisy and clusters with non-convex shapes data	Dalai and Senapati (2017)
Distance independence and correction algorithm	Maps point cloud to image and adjusts the target position	Insufficient information to state the advantages and limitation		He et al. (2021)
Levenberg–Marquardt Back-propagation	Optimise and train ANN	Fast for sum-of-squared-error type functions	Not recommended for large data sets	Demmers et al. (2018), Buayai et al. (2019)
Bayesian regulation Back-propagation	Optimise and train ANN	Probabilistic model, Useful for very large data sets	May assume that all features are independent	Suwannakhun and Daungmala (2018), Rana (2020)

broiler birds using Kinect depth camera with a R^2 of 0.94. MATLAB was applied to create an algorithm based on body dimensions, projected body volume, and dorsal area which was correlated with the measured weight using a multi-linear regression model. Jun et al. (2018) also considered the features derived after image segmentation as input and activated a fully connected neural network with single node output layer to predict LW of pigs.

Kashiha et al. (2014) estimated image-based individual weight of pigs with an accuracy of 96.2% and an error of 1.23 kg individually; and 97.5% accuracy and an error of 0.82 kg at a group level. Ozkaya et al. (2016) also revealed that body measurements of cattle (body length, wither height, chest depth and hip height) can be accurately concluded from 2D digital image analysis with 90–98% accuracy. Jensen et al. (2018) reported that convoluted neural network (CNN) estimated LW of individual pigs with 95% R^2-value with ± 7 % mean error between the predicted and observed LWs. Kongsro (2014) reported RMSE of 4.8% (3.38 kg) and a R^2 of 0.99 for estimation of LW by 3D cameras in 71 pigs. Condotta et al. (2018) performed a similar study with pigs and reported a R^2 of 0.99 with an error of 3.13 kg. Fernandes et al. (2019) divided the set of extracted features into two classes: body measurements, and shape descriptors. The body measurements extracted were area, volume, length, width and height resulting in R^2 in the range of 0.86–0.94, and 0.70–0.84 for the dataset with and without nursery pigs, respectively. The shape descriptors used by Fernandes and co-workers were eccentricity and Fourier descriptors. Eccentricity is a measurement of roundness which is estimated as the ratio between the foci and the major axis that has the same second moments as the pig (reflecting pixel distribution with respect to an arbitrary axis) of the ellipse while Fourier descriptor is a class of global image descriptors typically used for shape analysis and image matching (Burger and Burge, 2016).

Suwannakhun and Daungmala (2018) used a back-propagation algorithm to create a multiple-hidden layer network of sigmoidal neurons and an output layer of linear neurons which was trained by supervised learning method. Multiple neuron layers with nonlinear TF aided in learning nonlinear and linear relation of input and output vectors.

CNNs are another class of deep learning artificial neural network that has been recently emerging in the livestock image processing sector. The representation of a CNN for image processing of pigs for LW estimation has been shown in Fig. 4. CNNs once trained can function in real time and accurately identify pigs with an accuracy of about 96.7% allowing animal identification without RFID tags, for the purpose of monitoring welfare and growth (Albawi et al., 2017). Multiple output regression CNNs have been widely adapted that can extract information from images in an end-to-end manner with a rapid processing speed. It is able to extract body shape features and estimate pig weight and body size quickly and accurately with simple automated pre-processing of 3D images. This ensures its real-time operation in commercial farms. 3D imaging also reduces the influence of light on the accuracy of weight estimation even when a small amount of pig data is collected and corrected for different breeds (Zhang et al., 2021). Image processing is

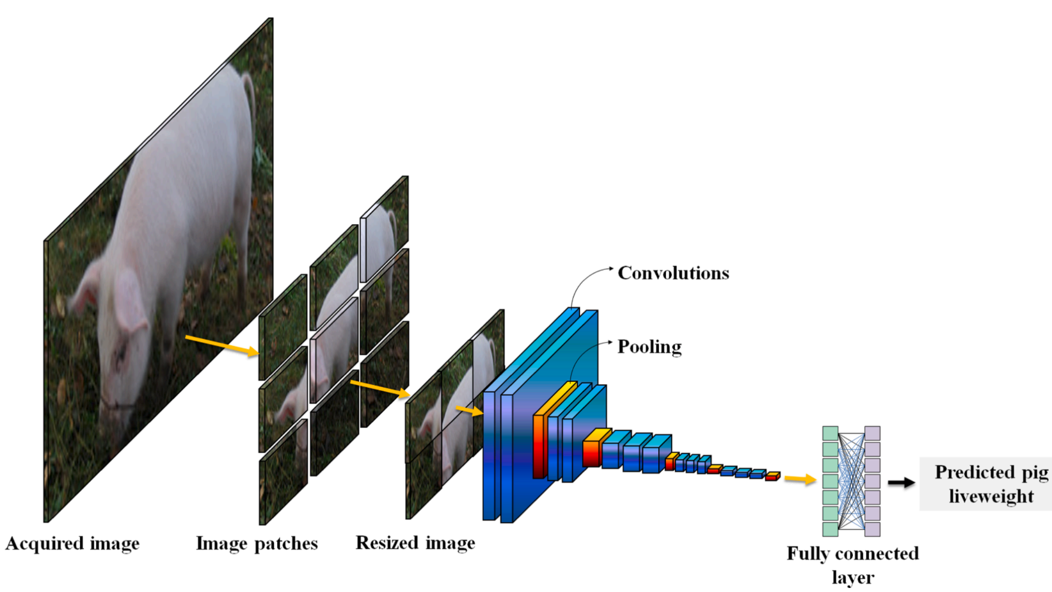


Fig. 4. Representative CNN infrastructure for prediction of pig liveweight.

considered sensitive to light interferences, making it less suitable for practical applications in grower/finisher herd in field conditions. In traditional image processing, image features such as lines and edges are extracted based on sharp colour contrasts. CNNs on the other hand, require no feature extraction and only very little pre-processing of images. Jensen et al. (2018) trained CNN to estimate the live weight of individual pigs with a R^2 of 95% and an error of ±7 %. They also observed that including reference images with no pigs in the training data results in better performance of CNN for live pig weight estimation.

4. Comparative evaluation of predictive model for pig liveweight estimation

Different statistical methods have been applied for assessment of LW using body measurements as per the goals and nature of the data collected. ANN has proved to be a more flexible system than multiple linear regression analysis as there is no need to satisfy assumptions, which is a mandate in regression analysis. Some of the studies comparing neural networks and linear regression analysis in the field of animal husbandry have been stated. However, Akkol et al. (2017) reported that ANN can be used as an alternative to multiple linear regression analysis with improved accuracy of prediction.

There are two main statistical methods to estimate weight in livestock, the first one based on statistical analysis such as correlation (Tadesse et al., 2012), simple (Parés et al., 2012), and multiple linear regression analysis (Eyduran et al., 2013; Seifemichael et al., 2014; Shi et al., 2016; Condotta et al., 2018; Pezzuolo et al., 2018c; Fernandes et al., 2019) and the second based on ANN (Wang et al., 2008; Wongsriworaphon et al., 2012, 2015; Jun et al., 2018). Linear regression models are said to yield beneficial outcomes in prediction of animals' LW (Yilmaz et al., 2013). Therefore, development of a regression model using linear body measurements to predict LW may lead to profitable returns in pig farming enterprises. Few related works suggested that ANN gave the least bias results for observed LW in broilers when compared to Gompertz equation (Roush et al., 2006). Similarly, Wang et al. (2008) in their research suggested that ANN can be a better model to predict accurate LW in pigs. Szyndler-Nedza et al. (2015) used ANN and regression analysis to predict carcass meat percentage in young pigs in which ANNs were found to be more accurate than the regression analysis method. The image based ANN model reported higher R^2 (0.892) in comparison to the regression analysis model (0.835) using the same variables. Kaewtapee et al. (2019) employed ANN for weight estimation of crossbred pigs and collected morphometric measurements of BL and HG. Thereafter, the image equations showed a higher accuracy ($R^2 = 0.866$) as compared to the HG ($R^2 = 0.760$) or BL ($R^2 = 0.721$) equations as well as the equation involving both HG and BL ($R^2 = 0.835$). Moreover, the image based ANN model expressed a better R^2 (0.892) in comparison to the regression analysis model. Kashiha et al. (2014) evaluated TF models and compared it against a linear regression model and a non-linear mixed effects model to select the most appropriate model in estimating pig's LW. The results indicated that TF model yielded a higher R^2 of 0.975 with low errors proving higher reliability of ANN methods. The superior performance of the non-linear image based regression model is related to the large amount of data arising from its non-contact analysis. Pezzuolo et al. (2018c) correlated the extracted dimensions to animal weight, and developed a linear and a non-linear model. It was found that both the models highly correlated with the ground-scale weight measurements with $R^2 > 0.95$. The MAE reduced to over 40% especially, in depth camera based non-linear model as compared to the non-linear model based on same manual measurements. A strong regression between manually measured body measurements (BL and WH) and the computed values of image processing was found by Shi et al. (2016). The results of RMSE from a total of 1460 image samples signified that the estimated values were in close proximity with the actual weight with an accuracy of more than 90% based on binocular stereo vision system. Buayai et al. (2019) compared the accuracy between the pig weight estimation method based on statistical analysis and ANN. A mean absolute probability error of 3.84% with a R^2 of 0.66 was noticed which indicated that MLR was less accurate than ANN (MAPE of 2.84% with $R^2 = 0.84$). Rana (2020) also determined the market weight in Landly crossbred pigs using Canny edge detection and BR algorithm and obtained a R^2 of 62.38 % and RMSE of 10.01. Although the ANN model achieved higher R^2value and lower RMSE in comparison to MLR model, the lower R^2 value can be attributed to no control over light intensity, ceiling height and other imaging conditions. Zhang et al. (2021) achieved a R^2 value of ∼0.988–0.997 between the estimated and measured results and employed multiple output regression CNN method to predict pig weight. The modified Xception, Xception, ResNet152, and MobileNet V2 models were trained for pig weight estimation out of which the modified Xception model offered the most precise estimation of pig live weight.

5. Current challenges and future perspectives

The above discussion showed that the prediction of live weight in pigs can be achieved non-intrusively with application of image analysis while preventing frequent physical contact between animal handler and the pigs. However, few challenges should be taken into account in future research. To expand the scope of upcoming researches, inclusion of multiple pigs in one single image may need animal identification and tracking to avoid confusion. If only the partial pig bodies are captured, the problem can be addressed by carefully choosing, limiting, and customizing the space available for animals' movement in the proximity of the camera system. Other factors that affect the accuracy of the LW predictions are the presence of more than one animal in a camera's field of view and the background. These issues become prominent in automated systems which select images from continuous or motion sensor-triggered videos. The second challenge is the full-automation of the image acquisition process. The image analysis involves intervention or subjective selection of image quality to some extent to be applied to the farm environment. Although image-processing is quite an automated technique which aids in precision of the method, the image acquisition process involves a manual step for controlling the image captures. The actual body fat and lean content of pigs are important parameters in swine production which may not be reflected by resultant body weight to a great extent. To overcome such issues, side-view camera along with a top-view camera can be employed to reconstruct the 3D surface area of pigs, in order to obtain more quantifiable body conformation data. Image-based forecasting can be classified as one of the emerging precision livestock farming practices in recent times to collect body weight data more frequently than before and enhance swine production efficiency by promoting precision livestock farming. Moreover, it is important to collect the data in a free setting without much physical control but because of this the recorded frames for each animal are generally heterogeneous in number as recording time for each pig varies and few animals end up with just a few frames captured. The most common reasons for lesser number of frames may be because of inappropriate standing position of the animals or that the animal passes too quickly over the area. Moreover, the proposed ANN models might need to be adapted and calibrated to the specific breed considered. The camera calibration often fails due to the excessive acquisition of grid images and the change of grid angle intermittently. The matching of images taken by multiple cameras is also a challenging procedure and needs standardization with respect to the herd size of pigs. It is imperative for image acquisition technologies applied at farm levels to be of practical utility and cost effective. An imaging system suitable for large herd size in commercial farms needs to be designed. In this regard, a light weight, portable, continuous imaging capturing system (in-out passage type) that can be mobilized as per requirements should be developed for a stress free and cost effective estimation of pig live weight in a natural environment. Moreover, innovative electronic components and new technologies should be implied such as 3D and Kinect cameras to elude the complicated calibrations.

6. Conclusions

The major contribution of machine vision-based imaging system of weighing of pigs has been in the development of a protocol which enables non-contact, least intrusive weighing of a pig in its natural state while walking where the pigs could move around anywhere in the pen or along the passages. Therefore, an image capture system can make the weighing process much easier for the stockman with least stress to both animal and the animal handler. Due to these aids, pigs do not essentially need to be placed in narrow spaces or enforced to be in a specific posture during image capture, which helps to reduce stress of the weighing process. It has also provided necessary technical innovation for the development of a cost effective, stress free and animal welfare oriented method for accurate estimation of pig LW. Therefore, the existing approach moves towards the implementation of a CVS for the acquisition of biometric traits and LW on commercial farms. It enables the collection of larger data in a short span of time and is not affected by technical hitches associated with scale reading or errors caused by animal movements. The software and hardware combination in this technique facilitates day to day availability of relevant data of pigs to the farm manager and assists in improving the nutrition and prevention of diseases, immediately and effectively. This method enables the farmer to quickly gain the LW of pigs with ease which is practically of prime importance to pig producers. This concept can help to build a proper procurement plan for pork processing industry by improving the precision of pig size measurements and offers potential cost reduction.

Declaration of Competing Interest

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

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