

## Review

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# The livestock farming digital transformation: implementation of new and emerging technologies using artificial intelligence

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**Abstract**

Livestock welfare assessment helps monitor animal health status to maintain productivity, identify injuries and stress, and avoid deterioration. It has also become an important marketing strategy since it increases consumer pressure for a more humane transformation in animal treatment. Common visual welfare practices by professionals and veterinarians may be subjective and cost-prohibitive, requiring trained personnel. Recent advances in remote sensing, computer vision, and artificial intelligence (AI) have helped developing new and emerging technologies for livestock biometrics to extract key physiological parameters associated with animal welfare. This review discusses the livestock farming digital transformation by describing (i) biometric techniques for health and welfare assessment, (ii) livestock identification for traceability and (iii) machine and deep learning application in livestock to address complex problems. This review also includes a critical assessment of these topics and research done so far, proposing future steps for the deployment of AI models in commercial farms. Most studies focused on model development without applications or deployment for the industry. Furthermore, reported biometric methods, accuracy, and machine learning approaches presented some inconsistencies that hinder validation. Therefore, it is required to develop more efficient, non-contact and reliable methods based on AI to assess livestock health, welfare, and productivity.

**Introduction**

Climate change predictions that are affecting most agricultural regions and livestock transportation routes are related to increasing ambient temperatures, rainfall variability, water availability, and increased climatic anomalies, such as heatwaves, frosts, bushfires, and floods, affecting livestock health, welfare, and productivity. These events have triggered and prioritized a critical digital transformation within livestock research and industries to be more predictive than reactive, implementing new and emerging technologies on animal monitoring for decision-making purposes. Several advances in smart livestock monitoring aim for the objective measurement of animal stress using digital technology to assess the effect of livestock welfare and productivity using biometrics and artificial intelligence (AI).

The most accurate methods to measure livestock health and welfare are invasive tests, such as analysis of tissue and blood samples, and contact sensors positioned on the skin of animals or internally either by minor surgery, intravaginal, or rectally implanted (Jorquera-Chavez *et al.*, 2019a; Zhang *et al.*, 2019b; Chung *et al.*, 2020). However, these are apparently impractical approaches to monitor many animals for continuous assessments on farms. These approaches require a high level of know-how by personnel for sampling, sensor placement, data acquisition processing, analysis and interpretation. Furthermore, they impose medium to high levels of stress on animals, introducing biases in the analysis and interpretation of data; for this reason, researchers are focusing on developing novel contactless methods to improve animal welfare (Neethirajan and Kemp, 2021). There are also visual assessments that can be made by experts and trained personnel to assess levels of animal stress and welfare. However, these can be subjective and require human supervision and assessment with similar disadvantages of the aforementioned physiological assessments and sensor technologies (Burn *et al.*, 2009).

Recent digital advances in sensor technology, sensor networks with The Internet of Things (IoT) connectivity, remote sensing, computer vision and AI for agricultural and human-based applications have allowed the potential automation and integration of different animal science and animal welfare assessment approaches (Morota *et al.*, 2018; Singh *et al.*, 2020). There has been increasing research on implementing these new and emerging digital technologies and

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adaption to livestock monitoring, such as minimal contact sensor technology, digital collars and remote sensing (Karthick *et al.*, 2020). Furthermore, novel analysis and modeling systems have included machine and deep learning modeling techniques to obtain practical and responsible AI applications. The main applications for these technologies have been focused on assessing physiological changes from animals to be related to different types of stress or the early prediction of diseases or parasite infestation (Neethirajan *et al.*, 2017; Neethirajan and Kemp, 2021). One of the most promising approaches is implementing AI incorporating remote sensing and machine learning (ML) modeling strategies to achieve a fully automated system for non-invasive data acquisition, analysis, and interpretation. Specifically, this approach is based on inputs from visible, thermal, multispectral, hyperspectral cameras and light detection and ranging (LiDAR) to predict targets, such as animal health, stress, and welfare parameters. This approach is presented in detail in the following sections of this review.

However, much of the research has been based on academic work using the limited amount of data accumulated in recent years to test mainly different AI modeling techniques rather than deployment and practical application to the industry. Some research groups have focused their efforts on pilots for AI system deployments to assess the effects of heat stress on animals and their respective production, welfare on farming and animal transport, animal identification for traceability, and monitoring greenhouse emissions to quantify and reduce the impact of livestock farming on climate change.

This review is based on the current research on these new and emerging digital technologies applied to livestock farming to assess health, welfare, and productivity (Table 1). Some AI-based research applied for potential livestock applications have tried to solve too many complex problems rather than concentrating on simple and practical applications, and with few deployment examples. However, the latter is a generalized problem of AI applications within all industries, in which only 20% of AI pilots, have been applied to real-world scenarios and have made it to commercial production. The latter figures have increased slightly due to COVID-19 for 2021, with increases up to 20% for ML and 25% for AI deployment solutions, according to the Hanover Enterprise Financial Decision Making 2020 report (Wilcox, 2020). By establishing a top-down approach (identifying goldilocks problems), specific and critical solutions could be easily studied to develop effectively new and emerging technologies, including AI. In Australia and worldwide, several issues have been identified for livestock transport in terms of the effect of climate change, such as effects of increased temperatures, droughts, and heatwaves on livestock welfare; especially during long sea trips through very hot transport environments, such as those in the Persian Gulf, with temperatures reaching over 50°C) and the identification and traceability of animals. Many livestock producing countries have identified AI and a digital transformation as an effective and practical solution for many monitoring and decision-making problems from the industry.

### Biometric techniques for health and welfare assessment

The most common methods for animal welfare and health assessment are either visual and subjective, specifically for animal behavior, or invasive. They may involve collecting blood or urine samples to be analyzed using expensive and time-consuming laboratory techniques such as enzyme-linked

immunosorbent assay (ELISA) and polymerase chain reaction (PCR) (Neethirajan *et al.*, 2017; Du and Zhou, 2018; Neethirajan, 2020). Other measurements that are usually related to the health and welfare of animals are based on their physiological responses such as body temperature, heart rate (HR), and respiration rate (RR) (Fuchs *et al.*, 2019; Halachmi *et al.*, 2019). To measure body temperature, the most reliable methods are intravaginal or measured in the ear, with the most common devices based on mercury or digital thermometers (Jorquera-Chavez *et al.*, 2019a; Zhang *et al.*, 2019b). Body temperature is vital for early detection and progression of heat stress, feed efficiency, metabolism, and disease symptoms detection such as inflammation, pain, infections, and reproduction stage, among others (McManus *et al.*, 2016; Zhang *et al.*, 2019b).

Traditional techniques to assess HR may involve manual measurements using stethoscopes (DiGiacomo *et al.*, 2016; Jorquera-Chavez *et al.*, 2019b; Fuentes *et al.*, 2020a), or automatic techniques based on electrocardiogram (ECG) devices, such as commercial monitor belts with chest electrodes, such as the Polar Sport Tester (Polar Electro Oy, Kempele, Finland) (Orihuela *et al.*, 2016; Stojkov *et al.*, 2016), and photoplethysmography (PPG) sensors attached to the ear (Nie *et al.*, 2020). The HR parameter and variability are usually used as an indicator of environmental stress, gestation period, metabolic rate, and diagnosis of cardiovascular diseases (Fuchs *et al.*, 2019; Halachmi *et al.*, 2019). On the other hand, RR is typically measured by manually counting the flank movements of animals resulting from breathing in 60 s using a chronometer (DiGiacomo *et al.*, 2016; Fuentes *et al.*, 2020a) or counting the breaths in 60 s using a stethoscope, or by attaching sensors in the nose, or thorax, which can detect breathing patterns (Jorquera-Chavez *et al.*, 2019a). Respiration rate can be used to indicate heat stress and respiratory diseases (Mandal *et al.*, 2017; Slimen *et al.*, 2019; Fuentes *et al.*, 2020a).

The main disadvantage of traditional methods based on contact or invasive sensors to assess physiological responses is the potential stress they can cause to the animal by the methodology used, which can introduce bias. The stress may be caused by the anxiety provoked by the restraint and manipulation/contact with their bodies for the actual measurement or to attach different sensors. Furthermore, these methods tend to be costly and time-consuming, making it very impractical assessing a large group of animals. In manual measurements, they may also have human error and, therefore, are subjective and not that reliable. Some specific applications for different livestock will be discussed, separating cattle, sheep and pigs (Table 1).

### Cattle

To assess the body temperature of cattle continuously, Chung *et al.* (2020) proposed an invasive method for dairy cows by implanting a radio frequency identification (RFID) biosensor (RFID Life Chip; Destron Fearing™, Fort Worth, TX, USA) on the lower part of ears of three cows that were monitored for 1 week; however, this method showed medium-strength correlations when compared directly to the intravaginal temperature probe for two of the cows ( $R^2 = 0.73$ ) and low correlation in the third cow ( $R^2 = 0.34$ ). The authors then developed a ML model based on the long short-term memory method to increase prediction accuracy. However, the study only reported the root mean squared error (RMSE = 0.081) of the model but left out the accuracy based on the correlation coefficient as it should be done for

**Table 1.** Summary of biometric methods to assess health and welfare for cattle, sheep, and pigs

Animals	Measurement	Technique	Groundtruth (traditional methods)	Number of animals	Accuracy of method	Proposed application	Reference
Cattle							
Dairy cows	Body temperature	Implanted RFID biosensor and Machine learning	Vaginal temperature (probe)	3	RMSE = 0.08	First steps for precision agriculture methods	(Chung <i>et al.</i> , 2020)
Simulated cows	Temperature and movements	Wearable digital sensors Wireless data acquisition	None	1 toy simulating a cow and hot water	Not reported	Health monitoring and disease detection	(Tahsin, 2016)
Cattle (Holstein and Jersey)	Body temperature	Contactless biometrics Computer vision Infrared thermal images	Rectal temperature (probe)	Not specified	Mean difference between methods 0.04 ± 0.10°C	Alternative to traditional temperature methods	(Wang <i>et al.</i> , 2021a)
German Holstein cows	HR HRV	Wearable sensors	None	40	Not reported	Tested impact of different stimulation methods	(Zipp <i>et al.</i> , 2018)
Dairy calves	HR	Wearable sensors	None	69	Not reported	Behavioral and stress response	(Buchli <i>et al.</i> , 2017)
Cows	HR RR Chewing	Contactless biometrics Computer vision RGB images and laser	HR: wearable sensor RR and Cheiwng: manual count	6	HR: $R = 0.98$ RR: $R = 0.97$ Chewing: $R = 0.99$	Biomedical monitoring for optimized cattle treatment	(Beiderman <i>et al.</i> , 2014)
Dairy cows Holstein Friesian	Skin temperature HR RR	Contactless biometrics Computer vision Infrared thermal images and RGB videos	Skin temperature: vaginal probe HR: wearable sensors RR: manual count	10	Skin Temperature: $R = 0.74$ HR: $R = 0.20-0.83$ RR: $R = 0.87$	Monitoring of physiological responses	(Jorquera-Chavez <i>et al.</i> , 2019b)
Dairy cows	RR	Computer vision Infrared thermal and RGB videos	Manual count	15	Mean difference Manual vs RGB video: $-0.01 \pm 0.87$ Manual vs infrared videos: $0.83 \pm 0.57$	Monitoring of health and welfare	(Stewart <i>et al.</i> , 2017)
Calves	RR	Contactless biometrics Computer vision Infrared thermal images	Manual count from RGB videos	5	$R^2 = 0.93$	Monitoring of health and welfare	(Lowe <i>et al.</i> , 2019)
Japanese Black Calves	RR	Contactless biometrics Computer vision Infrared thermal images Deep learning	Manual count	5	$R^2 = 0.91$	Monitoring health	(Kim and Hidaka, 2021)

(Continued)

**Table 1.** (Continued.)

Animals	Measurement	Technique	Groundtruth (traditional methods)	Number of animals	Accuracy of method	Proposed application	Reference
Qinchuan cattle	Body measurements (dimensions)	Contactless biometrics Computer vision RGB images	Manual measurements	3	2 mm	Contactless body measurements of large livestock	(Huang <i>et al.</i> , 2018)
Dairy cows	Drinking behavior	Integrated sensor module Computer vision Deep learning	None	25	Not reported	Automatic and quantitative assessment of drinking behavior as a measure of heat stress	(Tsai <i>et al.</i> , 2020)
Sheep							
Dairy sheep	Behavior activities	Wireless system Wearable sensors RGB videos	Manual assessment	3	93%	Behavior assessment	(Giovanetti <i>et al.</i> , 2017)
Ewes	Behavior activities	Wearable sensors RGB videos Machine learning	Manual assessment	6	85%	Assessment of sheep activity previous to methane measurements Assessment of temporal grazing patterns	(Alvarenga <i>et al.</i> , 2016)
Ewes	Body temperature	Wearable sensor	None	15	Not reported	Measurement of temperature changes in lambing period	(Abecia <i>et al.</i> , 2020)
Ewes	Surface temperature of different areas (anus, vulva, muzzle, eyes)	Contactless biometrics Computer vision Infrared thermal images	Rectal and vaginal temperature	20	Not reported	Assessment of temperature during estrous cycle Reproductive management	(de Freitas <i>et al.</i> , 2018)
Ewes	Eye temperature HR HRV	Computer vision Infrared thermal images Wearable sensors	None	20	Not reported	Assessment of autonomic nervous system responses	(Sutherland <i>et al.</i> , 2020)
Meat sheep	Skin temperature HR	Wireless wearable monitoring system	Traditional veterinary monitors	60	Non-significant differences (no p-value reported)	Assessment of physiological responses with minimal stress	(Cui <i>et al.</i> , 2019)
Mutton sheep	HR Oxygen saturation Body temperature	Wearable sensors	None	Not reported	Not reported	Diagnose survival status during transportation	(Zhang <i>et al.</i> , 2020)
Merino lambs	Skin temperature HR RR	Contactless biometrics Computer vision Machine learning	Skin and rectal temperature (digital thermometer) Stethoscope Manual count	12 sheep /3 times a day /four weeks	Skin temperature: $R^2 = 0.99$ HR and RR: $R = 0.94$	Assessment of physiological responses and heat stress during transportation	(Fuentes <i>et al.</i> , 2020a)
Sheep	Body measurements (dimensions; weight)	Contactless biometrics Computer vision Machine learning	Manual measurements	27	Weight: $R = 0.99$ Dimensions: $R = 0.79$	Increase efficiency in herds management	(Zhang <i>et al.</i> , 2018)

Pigs							
Pigs	Behavior	Contactless biometrics Computer vision	None	10 pigs /2 replications	Not reported	Assessment of heat stress	(Byrd <i>et al.</i> , 2020)
Pigs	Lying behavior	Contactless biometrics Computer vision	Not reported	88	96%	Welfare assessment	(Nasirahmadi <i>et al.</i> , 2017)
Pigs	Body measurements (dimensions) Weight estimation	Contactless biometrics Computer vision	Manual measurements	78	$R^2 > 0.95$ to predict weight	Estimate pigs' weight during weaning period	(Pezzuolo <i>et al.</i> , 2018)
Piglets Sus Scrofa	Skin temperature Cold/heat stress Thirst stress Hunger stress Pain stress	Contactless biometrics Computer vision Infrared thermal images Machine learning	Stress conditions based on treatments	72	Cold/heat stress: 100% Thirst stress: 91% Hunger stress: 86% Pain stress: 50%	Assessment of stress during handling and transportation	(da Fonseca <i>et al.</i> , 2020)
Sows	Rectal temperature	Contactless biometrics Computer vision Infrared thermal images Machine learning	Rectal temperature (mercury thermometer)	99	$R^2 = 0.80$	Welfare assessment	(Feng <i>et al.</i> , 2019)
Pigs	HR	Contactless biometrics Computer vision	Electrocardiogram	2	78% (Green color channel)	Real-time monitoring of health and welfare	(Wang <i>et al.</i> , 2021b)
Pigs	HR RR	Contactless biometrics Computer vision Infrared camera	Electrocardiogram Ventilator data	17	HR: $R^2 = 0.96$ RR: $R^2 = 0.97$	Long term monitoring of research animals	(Barbosa Pereira <i>et al.</i> , 2019)
Pigs	Skin temperature HR RR	Contactless biometrics Computer vision Infrared thermal images and RGB videos	None	46	Not reported	Early detection of disease before symptoms appear	(Jorquera-Chavez <i>et al.</i> , 2020)
Pigs	Eye temperature HR RR	Contactless biometrics Computer vision Infrared thermal and RGB videos	Stethoscope Manual count from videos	28	Eye temperature: not reported HR and RR: $R = 0.61-0.66$	Physiological responses due to respiratory diseases	(Jongman <i>et al.</i> , 2020)

\* Abbreviations: RFID, radio frequency identification; RMSE, root mean squared error; HR, heart rate; HRV, heart rate variability; RR, respiration rate; RGB, red, green, blue.

regression ML models. On the other hand, Tahsin (2016) developed a remote sensor system named Cattle Health Monitor and Disease Detector, connected using a wireless network. This system integrated a DS1620 digital thermometer/thermostat (Maxim Integrated™, San Jose, CA, USA) and a Memsic 2125 thermal accelerometer (Parallax, Inc., Rocklin, CA, USA) to assess the activity of animals by measuring the lateral and horizontal movements of the cow. The integrated sensors node was placed on the neck using a collar, with the option to be powered using a solar panel. Furthermore, Wang *et al.* (2021a) developed a non-invasive/contactless sensor system to assess the body temperature of cattle using an infrared thermal camera (AD-HF048; ADE Technology Inc., Taipei, Taiwan), an anemometer (410i; Testo SE & Co., Kilsyth, VIC, Australia), and a humidity sensor (RC-4HA; Elitech Technology, Inc., Milpitas, CA, USA). These sensors were placed in the feedlot at 1 m from the cows and 0.9 m above the ground to record the head of each cow, while these were restrained using a headlock. The authors used a rectal thermometer as groundtruth to validate the method and reported a difference of  $0.04 \pm 0.10^\circ\text{C}$  between the groundtruth and the method proposed. The anemometer and humidity sensor were used to remove the frames affected by external weather factors to extract outliers.

In the case of HR, Zipp *et al.* (2018) used Polar S810i and RS800CX sensors attached to the withers and close to the heart to measure HR and HR variability (HRV) while locked after milking to assess the impact of different stimulation methods (acoustic, manual and olfactory). However, the authors reported technical problems to acquire HR and HRV, which led to missing values and altered the analysis. This is another drawback of using contact sensors as they can become unreliable due to different reasons, such as natural animal movements causing sensors to lose contact with the animal skin and connectivity problems. Buchli *et al.* (2017) used a Polar S810i belt attached to the torso of calves to measure HR while the animals were in their pen. However, similar to the previous study, these authors had errors in the data acquired and excluded data from eight calves. To avoid these problems, remote sensing methods have been explored, such as those developed by Beiderman *et al.* (2014), based on an automatic system to assess HR, RR and chewing activity using a tripod holding a PixeLink B741 camera (PixeLink, Rochester, NY, USA) and a Photop D2100 laser connected to a computer. The laser pointed at the neck and stomach of the cow. The acquired signal was analyzed using the 'findpeaks' Matlab® (Mathworks, Inc., Natick, MA, USA) function to assess HR from the neck area and RR and chewing from the stomach section. The authors reported a correlation coefficient  $R = 0.98$  for HR,  $R = 0.97$  for RR and  $R = 0.99$  for chewing data compared with manual measurements for RR and chewing and Polar sensor for HR. These latter methods may solve the contact problems and unreliability of data quality; however, they seem to still be manual methods requiring operators. The authors did not propose an automation system for measurements.

Jorquera *et al.* (2019b) also presented contactless methods to assess skin temperature, HR and RR of dairy cows using remote sensing cameras and computer vision analysis. These authors used a FLIR AX8 camera (FLIR Systems, Wilsonville, OR, USA) integrated into a Raspberry Pi V2.1 camera module to record infrared thermal images (IRTI) and RGB videos of the face of the cows while restrained in the squeeze chute. The IRTIs were analyzed automatically using the FLIR Atlas software development kit (SDK) for Matlab® and cropped the videos in the eye and ear sections. The RGB videos were used to assess HR using

the PPG method based on the luminosity changes in the green channel of the eye, forehead and full face of the cows; these signals were then further analyzed using a customized Matlab® code previously developed for people (Gonzalez Viejo *et al.*, 2018) and adapted for animals. On the other hand, the authors used a FLIR ONE camera to record non-radiometric videos of the cows. These were analyzed using Matlab® based on the change in pixel intensity in the nose section to measure the inhalations and exhalations from which RR was calculated.

Regarding the RR techniques, besides the manual counts usually conducted based on visual assessment of the flank movement of animals, researchers have also developed computer vision techniques, which aid in the reduction of human error and bias. Stewart *et al.* (2017) assessed 15 dairy cows using three comparative methods to determine RR with (i) manual counts of the flank movements by recording the time it took the cow to reach 10 breaths, (ii) manual counts of flank movements similar to method (i) but from an RGB video recorded using a high-dynamic-range (HDR) CX220E camera (Sony Corporation, Tokyo, Japan), and (iii) manual count of the air movement (temperature variations) from the nostrils. The latter was performed from infrared thermal videos recorded using a ThermoCam S60 camera (FLIR Systems, Wilsonville, OR, USA). The three methods showed similar responses with the highest average difference of  $0.83 \pm 0.57$  between methods (i) and (iii). Furthermore, Lowe *et al.* (2019) presented a similar approach but tested only in five calves. In the latter study, the two methods were (i) manual count of flank movements from an RGB video recorded using a Panasonic HCV270 camera (Panasonic, Osaka, Japan), which was made by recording the time taken for the calf to reach five breath cycles, and (ii) manual count of the thermal fluctuations (color changes) in the nostrils from infrared thermal images recorded using a FLIR T650SC camera. The Adobe Premiere Pro CC (Adobe, San Jose, CA, USA) was used for the manual counts for both methods. A high determination coefficient ( $R^2 = 0.93$ ) was reported comparing both methods. More recently, Kim and Hidaka (2021) used a FLIR ONE PRO infrared thermal camera to record IRTIs and RGB videos from the face of calves. The authors first measured the color changes from the nostril region manually as the time it took for the calf to complete five breaths. A mask region-based convolutional neural network (Mask R-CNN) and transfer learning were used to automatically develop a model using the RGB video frames to automatically detect and mask the calves' noses. Once the nose was detected and masked in the RGB videos, co-registered IRTIs were used to automatically extract the mean temperature of the region of interest. The authors reported an  $R^2 = 0.91$  when comparing the manual and automatic methods.

Besides those used to assess physiological responses, other biometrics have been explored to be applied in beef and dairy cattle. These methods consist of the use of biosensors and/or image/video analysis (remote sensing). For example, Huang *et al.* (2018) developed a computer vision method to assess body measurements (dimensions) of cattle using an O3D303 3D LiDAR camera to record the individual animal side view and post-processing using filter fusion, clustering segmentation and matching techniques. Tsai *et al.* (2020) developed an integrated sensor module composed of a Raspberry Pi 3B processing unit (Raspberry Pi Foundation, Cambridge, England), a Raspberry Pi V2 camera module and a BME280 temperature and relative humidity sensor for environmental measurement. This integrated module was placed on the top of the drinking troughs in a dairy

farm to record the drinking behavior of the cows. The authors then applied convolutional neural networks (CNN) based on Tiny YOLOv3 real-time object detection deep learning network for the head detection of cows to predict the drinking length and frequency which were found to be correlated with the temperature-humidity index (THI;  $R^2 = 0.84$  and  $R^2 = 0.96$ , respectively).

## Sheep

Researchers have been working on different techniques to assess sheep behavioral and physiological responses using contact and contactless sensors. Giovanetti *et al.* (2017) designed a wireless system consisting of a halter with a three-axis accelerometer ADXL335 (Analog Devices, Wilmington, MA, USA) attached; this was positioned in the lower jaw of dairy sheep to measure the acceleration of their movements on x-, y- and z-axes. Furthermore, the authors used a Sanyo VPC-TH1 camera (Sanyo, Osaka, Japan) to record videos of the sheep during feeding and manually assessed whether the animals were grazing, ruminating or resting as well as the bites per minute. Similarly, Alvarenga *et al.* (2016) designed a halter attached below the jaw of sheep; this halter had an integrated data logger Aerobtec Motion Logger (AML prototype V1.0, AerobTec, Bratislava, Slovakia), which is able to measure acceleration in x-, y- and z-axes transformed into North, East and Down reference system. Additionally, they recorded videos of the sheep using a JVC Everio GZR10 camera (JVC Kenwood, Selangor, Malaysia) to manually assess grazing, lying, running, standing and walking activities. These data were used to develop ML models to automatically predict activities, obtaining an accuracy of 85%.

Abecia *et al.* (2020) presented a method to measure the body temperature of ewes using a button-size data logger DS1921 K (Thermochron™ iButton®, Maxim Integrated, San Jose, CA, USA) taped under the tail of the animals. This sensor was able to record temperature data every 5 min. Using remote sensing, de Freitas *et al.* (2018) used a FLIR i50 infrared thermal camera to record images from different areas of the sheep: anus, vulva, muzzle, and eyes. The authors used the FLIR Quickreport software to manually select the different sections in each sheep and obtain each area's mean temperature. They concluded that the vulva and muzzle were the best areas to assess temperature during the estrous cycle in ewes. Sutherland *et al.* (2020) also used an infrared thermal camera (FLIR Thermacam S60) to record videos of the left eye of ewes. These videos were analyzed to assess eye temperature using the Thermacam Researcher software ver. 2.7 (FLIR Systems, Wilsonville, OR, USA). Additionally, the authors used a Polar RS800CX sensor and placed it around the ewes thorax to assess HR and HRV.

In terms of potential applications of sensor technology, Cui *et al.* (2019) developed a wearable stress monitoring system (WSMS) consisting of master and slave units. The master unit was comprised of environmental sensors such as temperature, relative humidity and global positioning system (GPS) attached to an elastic band and placed around the rib cage of sheep, while the slave unit was composed of physiological sensors such as an open-source HR sensor (Pulse Sensor, World Famous Electronics LLC, New York, NY, USA), and a skin temperature infrared sensor (MLX90615; Melexis, Ypres, Belgium). This system was tested on meat sheep during transportation and proposed as a potential method to assess physiological responses with minimal stress. Zhang *et al.* (2020) designed a wearable collar that

included two sensors to measure (i) HR and oxygen saturation in the blood (MAX30102; Max Integrated, San Jose, CA, USA), and (ii) body temperature (MLX90614; Melexis, Ypres, Belgium). These sensors were connected to the Arduino Mobile App (Arduino LLC, Boston, MA, USA) through Bluetooth® for real-time monitoring and used an SD card for data storage. The authors also proposed this system to assess physiological responses during the transportation of sheep. However, these studies can only monitor sentinel animals, making it laborious, difficult and impractical for the assessment of all animals transported.

To solve the later problem, Fuentes *et al.* (2020a) presented a contactless/non-invasive method to assess temperature, HR and RR of sheep using computer vision analysis and ML. The authors used a FLIR DUO PRO camera to simultaneously record RGB and infrared thermal videos of sheep. The infrared thermal videos were analyzed using customized Matlab® R2020a algorithms to automatically recognize the sheep's head and obtain the maximum temperature. Results showed a very high correlation ( $R^2 = 0.99$ ) between the temperatures obtained with the thermal camera and the rectal and skin temperatures measured using a digital thermometer. On the other hand, RGB videos were analyzed using customized Matlab® R2020a codes to assess HR and RR based on the PPG principle using the G color channel from RGB scale for HR and 'a' from Lab scale for RR. An artificial neural network model was developed using the Matlab® code outputs to predict the real HR and RR (measured manually), obtaining high accuracy of  $R = 0.94$ . This study also proposed a potential deployment system to be used for animals in transport.

For other biometric assessments, Zhang *et al.* (2018) developed a computer vision method to measure the dimensions of sheep using three MV-EM120C Gigabit Ethernet charge-coupled device (CCD) cameras (Lano Photonics, JiLin Province, China) located at different positions (top, left and right side) of the weighing scale for sheep. The recorded images were analyzed in Matlab® R2013 using the superpixel segmentation algorithm. The authors also obtained the dimension parameters manually and found correlations of  $R = 0.99$  for weight and  $R = 0.79$  for dimensions (width, length, height and circumference) using support vector machine.

## Pigs

Pigs are also commonly studied to develop biometric techniques to assess behavioral and physiological responses. For example, Byrd *et al.* (2020) used a KPC-N502NUB camera (KT&C, Fairfield, NJ, USA) mounted on top of the pigs' pens to assess pig behavior. The authors used the GeoVision VMS software (GeoVision Inc, Taipei, Taiwan) and assessed whether the pigs were active (standing or sitting) or inactive (lying sternal or lateral). Nasirahmadi *et al.* (2017) assessed the lying behavior of pigs using closed-circuit television (CCTV) with a Sony RF2938 camera above the pen. Matlab® software was used to analyze the videos using computer vision algorithms to detect the position of each pig and analyze the distance between each animal considering their axes, orientation and centroid. On the other hand, Pezzuolo *et al.* (2018) obtained body measurements and weight of pigs using a Kinect V1 depth camera (Microsoft Corporation, Redmond, WA, USA) positioned on the top and side of the pen. Videos were analyzed using the Scanning Probe Image Processor (SPIP™) software (Image Metrology, Lyngby, Denmark) to obtain length, front and back height, and heart girth. Furthermore, authors developed linear and non-linear

models to predict weight, obtaining an accuracy  $R^2 > 0.95$  in all modeling methods tested. The drawback that the authors mentioned from this technique is that the system can only record data from a single camera at a time because there is interference when using simultaneous data acquisition of the two cameras.

Regarding techniques to measure body/skin temperature from pigs, da Fonseca *et al.* (2020) used a Testo 876-1 handheld infrared thermal camera (Testo Instruments, Lenzkirch, Germany) to record images of piglets' full bodies. The IRSoft v3.1 software (Testo Instruments, Lenzkirch, Germany) was used to obtain the maximum and minimum skin temperature values. Rocha *et al.* (2019) presented a method to measure the body temperature of pigs using two IR-TCM284 infrared thermal cameras (Jenoptik, Jena, Germany). One camera was placed in the pen perpendicular to the pig's body, while the second one was positioned 2.6 m above the pigs in the loading alley for transportation. The areas of interest evaluated were neck, rump, orbital region, and the area behind the ears; these were manually selected using the IRT Cronista Professional Software v3.6 (Grayess, Bradenton, FL, USA) and extracting the minimum, maximum and mean temperatures. Authors found that the temperatures from the orbital region and behind the ears were the most useful to assess different types of stress (cold, heat, thirst, hunger, and pain) during handling and transportation. On the other hand, Feng *et al.* (2019) developed a computer vision and ML method to predict the rectal temperature of sows using a T530 FLIR infrared thermal camera to capture images. The FLIR Tools software (FLIR Systems, Wilsonville, OR, USA) was used to obtain the maximum and mean skin temperature in different areas such as ears, forehead, shoulder, back central and back end, and vulva. With these data, the authors developed a partial least squared regression (PLS) model to predict rectal temperature, obtaining an accuracy of  $R^2 = 0.80$ .

Wang *et al.* (2021b) developed a contactless method to assess HR of pigs using two different setups (i) a webcam C920 HD PRO (Logitech, Tainan, Taiwan) located on top of the operation table with an anesthetized pig and (ii) a Sony HDRSR5 Handycam located on a tripod above resting individual housing with a resting pig. Matlab® was used to analyze the videos by selecting and cropping the (i) neck for the first setup and (ii) abdomen, neck and front leg for the dual setup. The authors used the PPG principle with the three color channels of the RGB scale and found the G channel provided the most accurate results compared to measurements using an ECG. Barbosa Pereira *et al.* (2019) also developed a method using anesthetized pigs; they used a long wave infrared VarioCam HD head 820 S/30 (InfraTec GmbH, Dresden, Germany) to assess HR and RR. The videos were analyzed using Matlab® R2018a, and it included the segmentation using a multilevel Otsu's algorithm, region of interest (chest) selection, features identification and tracking using the Kanade-Lucas-Tomasi (KLT) algorithm, temporal filtering to measure trajectory and principal components analysis (PCA) decomposition and selection. This allowed them to obtain an estimated HR and RR at the selected frequency rates. The authors reported determination coefficients of  $R^2 = 0.96$  for HR compared to the ECG method and  $R^2 = 0.97$  for RR compared to ventilator data. Jorquera-Chavez *et al.* (2020) developed a contactless method to assess temperature, HR and RR of pigs using an integrated camera composed of a FLIR AX8 infrared thermal camera and a Raspberry Pi Camera V2.1 to record IRTIs and RGB videos, and a FLIR ONE infrared thermal camera to record non-radiometric videos. The authors used the same method as that reported for cows (Jorquera-Chavez *et al.*, 2019b) using Matlab®

R2018b selecting the eyes and ears as regions of interest for temperature, eye section for HR and nose for RR. The same method was used in the study developed by Jongman *et al.* (2020), but they used a FLIR DUO PRO R dual camera (infrared thermal and RGB) and reported a correlation coefficient within the  $R = 0.61-0.66$  range for HR and RR compared to manual measurements.

### Biometric techniques for recognition and identification

Correct and accurate identification of livestock is essential for farmers and producers. It also allows relating each animal to different productivity aspects such as health-related factors, behavior, production yield and quality and breeding. Furthermore, animal identification is essential for traceability, especially during transport and after selling, to avoid fraud and animal ledger or identification forging. However, traditional methods involve ear tags, tattoos, microchips and radio frequency identification (RFID) collars, which involve high costs, and some may be unreliable and easily hacked or interchanged. Furthermore, they require human labor for their maintenance, making them time-consuming, prone to human error and may lead to swapping tags (Awad, 2016; Kumar *et al.*, 2016, 2017a; Zin *et al.*, 2018). Therefore, some studies in recent years have focused on the development of contactless biometric techniques to automate the recognition and identification of different animals such as bears, using deep learning (Clapham *et al.*, 2020), and cows based on different features such as the face (Cai and Li, 2013; Kumar *et al.*, 2016), muzzle (Kumar *et al.*, 2017a), body patterns (Zin *et al.*, 2018), iris recognition (Lu *et al.*, 2014) or retinal patterns (Awad, 2016).

### Cattle

Most of these biometric techniques for recognition and identification have been developed for cattle. Authors have presented methods based on one of the three main techniques (i) muzzle pattern identification, (ii) face recognition and (iii) body recognition and identification. The first technique has been applied for cattle recognition using images of the muzzle and analyzed for features as it has a particular pattern that is different for each animal, similar to the human fingerprints. Once these features and patterns are recognized, a deep learning model is developed to identify each cow (Noviyanto and Arymurthy, 2012; Gaber *et al.*, 2016; Kumar *et al.*, 2017a, 2017b, 2018; Bello *et al.*, 2020). Face recognition methods using different techniques such as local binary pattern algorithms (Cai and Li, 2013) and CNN have been proposed for specific cattle breeds with different colors and patterns, such as Simmental (Wang *et al.*, 2020), Holstein, Guernseys and Ayrshires, among others (Kumar *et al.*, 2016; Bergamini *et al.*, 2018); however, none has been presented in single-coloured cattle breeds such as Angus. On the other hand, body recognition methods have been developed to identify cows within a herd using computer vision and deep learning techniques. Within the proposed methods are cattle recognition from the side (Bhole *et al.*, 2019), from behind (Qiao *et al.*, 2019), different angles (de Lima Weber *et al.*, 2020) or from the top (Andrew *et al.*, 2019). The latter was proposed to identify and recognize Holstein and Friesian cattle using an unmanned aerial vehicle (UAV) (Andrew *et al.*, 2017, 2019, 2020a, 2020b). Bhole *et al.* (2019) proposed an extra step for cow recognition from the side by recording IRTIs to ease the image segmentation and remove the background.



## Sheep

While biometrics applied for the identification and recognition of sheep have not been deeply explored, the development of some proposed methods has been published. The techniques that have been reported for sheep consist of retinal recognition using a commercial retinal scanner, OptiReader (Optibrand®, Fort Collins, CO, USA) (Barron *et al.*, 2008), and face recognition using classification methods such as machine or deep learning. Salama *et al.* (2019) developed a deep learning model based on CNN and Bayesian optimization and obtained an identification accuracy of 98%. Corkery *et al.* (2007) proposed a method based on independent components analysis and the InfoMax algorithm to identify the specific components from the normalized images of sheep faces and then find them in each tested image; the authors reported an accuracy within 95–95%.

## Pigs

The biometric techniques that have been published to identify pigs are based mainly on face recognition and body recognition from the tops of pens. Hansen *et al.* (2018) developed a face recognition method using CNN with high accuracy (97%). Marsot *et al.* (2020) developed a face recognition system based on a mix of computer vision to identify the face and eyes and deep learning CNN for classification purposes, obtaining an accuracy of 83%. On the other hand, Wang *et al.* (2018) proposed a method to identify pigs from images recorded from the whole body using integrated deep learning networks such as dual-path network (DPN131), InceptionV3 and Xception, with an accuracy of 96%. Huang *et al.* (2020) tested a Weber texture local descriptor (WTLD) identification method with different masks to detect and recognize individual features such as hair, skin texture, and spots using images of groups of pigs; the tested WTLD methods resulted in accuracies >96%. Kashiha *et al.* (2013) based their automatic identification method on computer vision to recognize marked pigs within a pen using the Fourier algorithm for patterns description and Euclidean distance, this technique resulted in 89% accuracy.

## Machine and deep learning application in livestock to address complex problems

This section concentrates specifically on the research on AI application using ML and deep learning modeling techniques on livestock, specifically for cattle, sheep and pigs. One of the latest research studies has been focused on the use of AI to identify farm animal emotional responses, including pigs and cattle (Neethirajan, 2021). However, it may be difficult to assess and interpret the emotional state of farm animals only from facial expression and ear positioning, as proposed in the latter study, and more objective assessment could be performed using targets based on hormonal measurements from endorphins, dopamine, serotonin and oxytocin among others, which will require blood sampling. Therefore, all the *in vitro* and tissue applications were excluded from this section because they require either destructive or invasive methods to obtain data.

## Cattle

A simple AI approach was proposed using historical data (4 years) with almost ubiquitous sensor technology in livestock farms, such as meteorological weather stations with daily temperature and

relative humidity (Fuentes *et al.*, 2020b). In this study, meteorological data was used to calculate temperature and humidity indices (THI) using different algorithmic approaches as inputs to assess the effect of heat stress on milk productivity as targets in a robotic dairy farm. This approach attempted to answer complex questions with potentially readily available data from robotic and conventional dairy farms and proposed a deployment system for an AI approach with a general accuracy of AI models of 87%. More accurate heat stress assessments could be achieved by either sensor technology, with minimal invasiveness to animals, such as ear clips, collars or similar, or remote sensing cameras, computer vision and deep learning modeling. However, the latter digital approach requires assessing individual animals using extra hardware and sensors, camera systems located in strategic positions allowing monitoring of every single animal (e.g. corral systems and straight alleys). Furthermore, these new digital approaches require the recording of new data. A big question in applications of AI in cattle, in this case, would be whether it is worth the significant extra investment in hardware and ML modeling using new data to increase the accuracy of models by an additional 10.

Sensor technology and sensor networks have been implemented in cattle to assess lameness, such as accelerometers, IoT connectivity and time series ML modeling approaches (Taneja *et al.*, 2020; Wu *et al.*, 2020). These applications were the first approaches to be implemented in animals after applications in humans for fitbits. Sensor readings and connectivity using IoT will facilitate the implementation of this technology in a near or real-time fashion. However, there is a big downside of the requirement of sensors for every single animal to be monitored. This is valid to other applications for sensor integration (Neethirajan, 2020), such as collars, halter and ear tag sensors (Rahman *et al.*, 2018), to detect physiological changes, behavior and other anomalies (Wagner *et al.*, 2020).

As mentioned before, animal recognition using deep learning approaches should be considered the first step to apply further remote sensing and AI tools. A second step should be the identification of key features from animals using deep learning (Jiang *et al.*, 2019), which makes possible the extraction of physiological information from those specific regions using ML modeling, such as HR from the eye section or exposed skin (e.g. ears or muzzle) and RR from the muzzle section. These animal features should be recognized in a video to extract enough information to obtain physiological parameters that currently require 4–8 s (e.g. HR and RR) for the signal to stabilize and get meaningful data. Hence, the AI implementation steps should consider animal recognition, specific feature recognition and tracking and extraction of physiological parameters using ML.

Integration of UAV, computer vision algorithms and CNN have been attempted for the recognition of cattle from the air (Barbedo *et al.*, 2019). However, these authors concentrated efforts on the feasibility and testing of different algorithms rather than the potential deployment of a pilot program. Furthermore, these approaches could also be used for animal recognition and the potential extraction of physiological parameters, such as body temperature (using infrared thermal cameras as payload). Dairy cows could offer more identification features than Angus cattle, which may require the implementation of multispectral cameras to include potential non-visible features from animals.

## Sheep

Sensor technology and sensor networks have also been applied in parallel with ML approaches for sheep using electronic collars and

ear sensors as input data and supervised selecting several behavior parameters as targets with a reported accuracy of <90% for both methods (Mansbridge *et al.*, 2018). Some predictive approaches from existing data have been attempted to assess carcass traits from early life animal records (Shahinfar *et al.*, 2019) using supervised and unsupervised regression ML methods with various low to high accuracies reported.

Similar detection systems mentioned before for other animals have been applied for sheep counting using computer vision and deep learning CNN methods (Sarwar *et al.*, 2018), which can also be used in parallel with other AI procedures to extract more information from animals for health or welfare assessments, such as sheep weight (Shah *et al.*, 2021). Following this approach, additional physiological parameters, such as HR, body temperature and RR, can be extracted from individual sheep non-invasively (Fuentes *et al.*, 2020a). The latter study also proposed using this AI approach for real livestock farming applications, such as animal welfare assessment for animals during transportation.

Other welfare assessments have been developed for sheep based on the facial classification expression for pain level applied using deep learning CNN and computer vision with 95% accuracy. However, no deployment was reported, which can be used to assess further animal welfare (Jwade *et al.*, 2019).

## Pigs

Some simple ML applications have been implemented to predict water usage in pig farms using regression ML algorithms (Lee *et al.*, 2017). However, this study reported a maximum determination coefficient of  $R^2 = 0.42$  for regression tree algorithms, which could be related to poor parameter engineering, since only temperature and relative humidity were used.

Automatic pig counting (Tian *et al.*, 2019), pig posture detection (Nasirahmadi *et al.*, 2019; Riekert *et al.*, 2020), mounting (Li *et al.*, 2019) and sow behavior (Zhang *et al.*, 2019a), localization and tracking (Cowton *et al.*, 2019) aggressive behavior (Chen *et al.*, 2020) have been attempted using computer vision and deep learning. These are relatively complex approaches for meaningful questions considering further pipeline of analyses. These approaches could be used to extract more information from the individual pigs once they have been recognized, such as biometrics, including HR and RR extracted for other animals such as sheep, mentioned before (Fuentes *et al.*, 2020a), and cattle identification (Andrew *et al.*, 2017) with accuracies in identification between 86 and 96% with a maximum of 89 individuals.

Other approaches have been implemented for the early detection (between 1 and 7 days of infection) of respiratory diseases in pigs using deep learning approaches (Cowton *et al.*, 2018). Other computer vision approaches using visible and infrared thermal imagery analysis without ML approaches also delivered an acceptable assessment of respiratory diseases in pigs (Jorquera-Chavez *et al.*, 2020).

## Conclusions

Implementing remote sensing, biometrics and AI for livestock health and welfare assessment could have many positive ethical implications and higher acceptability by consumers of different products derived from livestock farming. Specifically, integrating digital technologies could directly impact increasing the willingness to purchase products from sources that introduced AI to increase animal welfare on the farm and transport for ethical

and responsible animal handling and slaughtering. However, a systematic deployment of different digital technologies reviewed in this paper will require further investment, which some governments, such as Australia, have identified as a priority.

It is difficult to assess the applicability or deployment options from different research studies done so far on livestock, which have applied biometrics and AI, because there is no consistency in the reporting of the accuracy of models, performance, testing for over or underfitting of models, number of animals used or proposed pilot or deployment options (Table 1). Furthermore, in most of these studies, there are no follow-ups on the models either by establishing potential pilot deployments to test them in real-life scenarios. Many researchers only rely on the validation and testing protocols within the model development stage. The latter does not give any information on the practicality or applicability of these digital systems, because circumstances in real-life scenarios change over time and models need to be re-evaluated and continuously fed with new data to learn and adapt to different circumstances and scales of use.

It is also clear that most of the AI developments and modeling for livestock farming applications are academic, and very little research has focused on efficient and practical deployment to real-world scenarios. To change this, researchers should work on real-life problems in the livestock industry, starting with simple ones and pressing questions. The next step is to solve them using efficient and affordable technology, starting with big data analysis from historical data accumulated by different industries. The idea here is to initially apply AI where the data exists, to achieve maximum reach with high performance and scalable applications (e.g. heat stress assessment on milk production using historical weather information and productivity data). It is also required to check whether the correct data is available, avoid basing AI on reduced datasets, and restricted only to test different ML approaches. Academic exercises based on AI modeling for its sake only rarely reach pilot programs and applications in the field. Furthermore, data quality and data security are becoming fundamental issues that should be dealt using digital ledger systems for data and model deployments, such as blockchain implementation. This approach allows treating data and AI models as a currency to avoid hacking and adulteration, especially with AI models and data dealing with welfare assessments for animals in farms to claim ethical production or animals in transport.

To solve these problems, AI modeling, development and deployment strategies should have a multidisciplinary team with constant communication during the model development and deployment stages; what could be a better approach, but very rare nowadays is to have an expert on animal science, data analysis and AI dealing with companies. This could change soon through specialized Agriculture, Animal Science and Veterinary degrees in which data analysis, ML and AI are introduced in their respective academic curriculums.

Integrating new and emerging digital technology with AI development and deployment strategies for practical applications would create effective and efficient AI pilot applications that can be easily scaled up to production to create successful innovations in livestock farming.

## References

- Abecia JA, María GA, Estévez-Moreno LX and Miranda-De La Lama GC (2020) Daily rhythms of body temperature around lambing in sheep measured non-invasively. *Biological Rhythm Research* 51, 988–993.

- Alvarenga F, Borges I, Palkovič L, Rodina J, Oddy V and Dobos R (2016) Using a three-axis accelerometer to identify and classify sheep behaviour at pasture. *Applied Animal Behaviour Science* **181**, 91–99.
- Andrew W, Greatwood C and Burghardt T (2017) Visual localisation and individual identification of Holstein Friesian cattle via deep learning. *Proceedings of the IEEE International Conference on Computer Vision Workshops*, 2850–2859.
- Andrew W, Greatwood C and Burghardt T (2019) Aerial animal biometrics: individual Friesian cattle recovery and visual identification via an autonomous uav with onboard deep inference. *arXiv preprint arXiv*, 1907.05310.
- Andrew W, Gao J, Mullan S, Campbell N, Dowsey AW and Burghardt T (2020a) Visual identification of individual Holstein-Friesian cattle via deep metric learning. *arXiv preprint arXiv*, 2006.09205.
- Andrew W, Greatwood C and Burghardt T (2020b) Fusing animal biometrics with autonomous robotics: drone-based search and individual id of Friesian cattle. *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision Workshops* **1**, 38–43.
- Awad AI (2016) From classical methods to animal biometrics: a review on cattle identification and tracking. *Computers and Electronics in Agriculture* **123**, 423–435.
- Barbedo JGA, Koenigkan LV, Santos TT and Santos PM (2019) A study on the detection of cattle in UAV images using deep learning. *Sensors* **19**, 5436.
- Barbosa Pereira C, Dohmeier H, Kunczik J, Hochhausen N, Tolba R and Czaplík M (2019) Contactless monitoring of heart and respiratory rate in anesthetized pigs using infrared thermography. *PLoS One* **14**, e0224747.
- Barron UG, Corkery G, Barry B, Butler F, McDonnell K and Ward S (2008) Assessment of retinal recognition technology as a biometric method for sheep identification. *Computers and Electronics in Agriculture* **60**, 156–166.
- Beiderman Y, Kunin M, Kolberg E, Halachmi I, Abramov B, Amsalem R and Zalevsky Z (2014) Automatic solution for detection, identification and biomedical monitoring of a cow using remote sensing for optimised treatment of cattle. *Journal of Agricultural Engineering* **45**, 153–160.
- Bello R-W, Talib AZH and Mohamed ASAB (2020) Deep learning-based architectures for recognition of cow using cow nose image pattern. *Gazi University Journal of Science* **33**, 831–844.
- Bergamini L, Porrello A, Dondona AC, Del Negro E, Mattioli M, D'alterio N and Calderara S (2018) Multi-views embedding for cattle re-identification. 2018 14th International Conference on Signal-Image Technology & Internet-Based Systems (SITIS), 2018. IEEE, pp. 184–191.
- Bhole A, Falzon O, Biehl M and Azzopardi G (2019) A computer vision pipeline that uses thermal and RGB images for the recognition of Holstein cattle. *International Conference on Computer Analysis of Images and Patterns*, 2019. Springer, 108–119.
- Buchli C, Raselli A, Bruckmaier R and Hillmann E (2017) Contact with cows during the young age increases social competence and lowers the cardiac stress reaction in dairy calves. *Applied Animal Behaviour Science* **187**, 1–7.
- Burn CC, Pritchard JC and Whay HR (2009) Observer reliability for working equine welfare assessment: problems with high prevalences of certain results. *Animal Welfare* **18**, 177–187.
- Byrd C, Johnson J, Radcliffe J, Craig B, Eicher S and Lay Jr D (2020) Nonlinear analysis of heart rate variability for evaluating the growing pig stress response to an acute heat episode. *Animal: An International Journal of Animal Bioscience* **14**, 379–387.
- Cai C and Li J (2013) Cattle face recognition using local binary pattern descriptor. 2013 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference 29 Oct.-1 Nov. 2013, Kaohsiung, Taiwan. IEEE, 1–4.
- Chen C, Zhu W, Steibel J, Siegford J, Wurtz K, Han J and Norton T (2020) Recognition of aggressive episodes of pigs based on convolutional neural network and long short-term memory. *Computers and Electronics in Agriculture* **169**, 105166.
- Chung H, Li J, Kim Y, Van Os JM, Brounts SH and Choi CY (2020) Using implantable biosensors and wearable scanners to monitor dairy cattle's core body temperature in real-time. *Computers and Electronics in Agriculture* **174**, 105453.
- Clapham M, Miller E, Nguyen M and Darimont CT (2020) Automated facial recognition for wildlife that lack unique markings: a deep learning approach for brown bears. *Ecology and Evolution* **10**, 12883–12892.
- Corkery G, Gonzales-Barron UA, Butler F, Mc Donnell K and Ward S (2007) A preliminary investigation on face recognition as a biometric identifier of sheep. *Transactions of the ASABE* **50**, 313–320.
- Cowton J, Kyriazakis I, Plötz T and Bacardit J (2018) A combined deep-learning GRU-autoencoder for the early detection of respiratory disease in pigs using multiple environmental sensors. *Sensors* **18**, 2521.
- Cowton J, Kyriazakis I and Bacardit J (2019) Automated individual pig localisation, tracking and behaviour metric extraction using deep learning. *IEEE Access* **7**, 108049–108060.
- Cui Y, Zhang M, Li J, Luo H, Zhang X and Fu Z (2019) WSMS: wearable stress monitoring system based on IoT multi-sensor platform for living sheep transportation. *Electronics* **8**, 441.
- Da Fonseca FN, Abe JM, De Alencar Nääs I, Da Silva Cordeiro AF, Do Amaral FV and Ungaro HC (2020) Automatic prediction of stress in piglets (*Sus Scrofa*) using infrared skin temperature. *Computers and Electronics in Agriculture* **168**, 105148.
- De Freitas ACB, Vega WHO, Quirino CR, Junior AB, David CMG, Geraldo AT, Rua MAS, Rojas LFC, De Almeida Filho JE and Dias AJB (2018) Surface temperature of ewes during estrous cycle measured by infrared thermography. *Theriogenology* **119**, 245–251.
- De Lima Weber F, De Moraes Weber VA, Menezes GV, Junior ADSO, Alves DA, De Oliveira MVM, Matsubara ET, Pistori H and De Abreu UGP (2020) Recognition of pantaneira cattle breed using computer vision and convolutional neural networks. *Computers and Electronics in Agriculture* **175**, 105548.
- Digiacoimo K, Simpson S, Leury BJ and Dunshea FR (2016) Dietary betaine impacts the physiological responses to moderate heat conditions in a dose-dependent manner in sheep. *Animals* **6**, 51.
- Du X and Zhou J (2018) Application of biosensors to detection of epidemic diseases in animals. *Research in Veterinary Science* **118**, 444–448.
- Feng Y-Z, Zhao H-T, Jia G-F, Ojukwu C and Tan H-Q (2019) Establishment of validated models for non-invasive prediction of rectal temperature of sows using infrared thermography and chemometrics. *International Journal of Biometeorology* **63**, 1405–1415.
- Fuchs B, Sørheim KM, Chincarini M, Brunberg E, Stubbsjøen SM, Bratbergsgengen K, Hvasshovd SO, Zimmermann B, Lande US and Grøva L (2019) Heart rate sensor validation and seasonal and diurnal variation of body temperature and heart rate in domestic sheep. *Veterinary and Animal Science* **8**, 100075.
- Fuentes S, Gonzalez Viejo C, Chauhan SS, Joy A, Tongson E and Dunshea FR (2020a) Non-invasive sheep biometrics obtained by computer vision algorithms and machine learning modeling using integrated visible/infrared thermal cameras. *Sensors* **20**, 6334.
- Fuentes S, Gonzalez Viejo C, Cullen B, Tongson E, Chauhan SS and Dunshea FR (2020b) Artificial intelligence applied to a robotic dairy farm to model milk productivity and quality based on Cow data and daily environmental parameters. *Sensors* **20**, 2975.
- Gaber T, Tharwat A, Hassanien AE and Snael V (2016) Biometric cattle identification approach based on weber's local descriptor and adaboost classifier. *Computers and Electronics in Agriculture* **122**, 55–66.
- Giovanetti V, Decandia M, Molle G, Acciaro M, Mameli M, Cabiddu A, Cossu R, Serra M, Manca C and Rattu S (2017) Automatic classification system for grazing, ruminating and resting behaviour of dairy sheep using a tri-axial accelerometer. *Livestock Science* **196**, 42–48.
- Gonzalez Viejo C, Fuentes S, Torrico D and Dunshea F (2018) Non-contact heart rate and blood pressure estimations from video analysis and machine learning modelling applied to food sensory responses: a case study for chocolate. *Sensors* **18**, 1802.
- Halachmi I, Guarino M, Bewley J and Pastell M (2019) Smart animal agriculture: application of real-time sensors to improve animal well-being and production. *Annual Review of Animal Biosciences* **7**, 403–425.
- Hansen MF, Smith ML, Smith LN, Salter MG, Baxter EM, Farish M and Grieve B (2018) Towards on-farm pig face recognition using convolutional neural networks. *Computers in Industry* **98**, 145–152.
- Huang L, Li S, Zhu A, Fan X, Zhang C and Wang H (2018) Non-contact body measurement for Qinchuan cattle with LiDAR sensor. *Sensors* **18**, 3014.
- Huang W, Zhu W, Ma C and Guo Y (2020) Weber texture local descriptor for identification of group-housed pigs. *Sensors* **20**, 4649.

- Jiang B, Wu Q, Yin X, Wu D, Song H and He D (2019) FLYOLOV3 deep learning for key parts of dairy cow body detection. *Computers and Electronics in Agriculture* **166**, 104982.
- Jongman E, Jorquera-Chavez M, Dunshea F, Fuentes S, Poblete T, Rajasekhara R and Morisson R (2020) Developing Remote Monitoring Methods for Early Detection of Respiratory Disease in Pigs. Final Report A1-104, Australasian Pork Research Institute Limited (23 pp). <https://apri.com.au/wp-content/uploads/2021/06/A1-104-Final-Report.pdf>
- Jorquera-Chavez M, Fuentes S, Dunshea FR, Jongman EC and Warner RD (2019a) Computer vision and remote sensing to assess physiological responses of cattle to pre-slaughter stress, and its impact on beef quality: a review. *Meat Science* **156**, 11–22.
- Jorquera-Chavez M, Fuentes S, Dunshea FR, Warner RD, Poblete T and Jongman EC (2019b) Modelling and validation of computer vision techniques to assess heart rate, eye temperature, ear-base temperature and respiration rate in cattle. *Animals* **9**, 1089.
- Jorquera-Chavez M, Fuentes S, Dunshea FR, Warner RD, Poblete T, Morrison RS and Jongman EC (2020) Remotely sensed imagery for early detection of respiratory disease in pigs: a pilot study. *Animals* **10**, 451.
- Jwade SA, Guzzomi A and Mian A (2019) On-farm automatic sheep breed classification using deep learning. *Computers and Electronics in Agriculture* **167**, 105055.
- Karthick G, Sridhar M and Pankajavalli P (2020) Internet of things in animal healthcare (IoT/AH): review of recent advancements in architecture, sensing technologies and real-time monitoring. *SN Computer Science* **1**, 1–16.
- Kashiha M, Bahr C, Ott S, Moons CP, Niewold TA, Ödberg FO and Berckmans D (2013) Automatic identification of marked pigs in a pen using image pattern recognition. *Computers and Electronics in Agriculture* **93**, 111–120.
- Kim S and Hidaka Y (2021) Breathing pattern analysis in cattle using infrared thermography and computer vision. *Animals* **11**, 207.
- Kumar S, Tiwari S and Singh SK (2016) Face recognition of cattle: can it be done? *Proceedings of the National Academy of Sciences, India Section A: Physical Sciences* **86**, 137–148.
- Kumar S, Singh SK and Singh AK (2017a) Muzzle point pattern-based techniques for individual cattle identification. *IET Image Processing* **11**, 805–814.
- Kumar S, Singh SK, Singh RS, Singh AK and Tiwari S (2017b) Real-time recognition of cattle using animal biometrics. *Journal of Real-Time Image Processing* **13**, 505–526.
- Kumar S, Pandey A, Satwik KSR, Kumar S, Singh SK, Singh AK and Mohan A (2018) Deep learning framework for recognition of cattle using muzzle point image pattern. *Measurement* **116**, 1–17.
- Lee W, Ryu J, Ban T-W, Kim SH and Choi H (2017) Prediction of water usage in pig farm based on machine learning. *Journal of the Korea Institute of Information and Communication Engineering* **21**, 1560–1566.
- Li D, Chen Y, Zhang K and Li Z (2019) Mounting behaviour recognition for pigs based on deep learning. *Sensors* **19**, 4924.
- Lowe G, Sutherland M, Waas J, Schaefer A, Cox N and Stewart M (2019) Infrared thermography—a non-invasive method of measuring respiration rate in calves. *Animals* **9**, 535.
- Lu Y, He X, Wen Y and Wang PS (2014) A new cow identification system based on iris analysis and recognition. *International Journal of Biometrics* **6**, 18–32.
- Mandal R, Gupta V, Joshi V, Kumar S and Mondal D (2017) Study of clinico-hematobiochemical changes and therapeutic management of naturally infected cases of respiratory disease in Non-descript goats of bareilly region. *International Journal of Livestock Research* **7**, 211–218.
- Mansbridge N, Mitsch J, Bollard N, Ellis K, Miguel-Pacheco GG, Dottorini T and Kaler J (2018) Feature selection and comparison of machine learning algorithms in classification of grazing and rumination behaviour in sheep. *Sensors* **18**, 3532.
- Marsot M, Mei J, Shan X, Ye L, Feng P, Yan X, Li C and Zhao Y (2020) An adaptive pig face recognition approach using convolutional neural networks. *Computers and Electronics in Agriculture* **173**, 105386.
- Mcmanus C, Tanure CB, Peripolli V, Seixas L, Fischer V, Gabbi AM, Menegassi SR, Stumpf MT, Kolling GJ and Dias E (2016) Infrared thermography in animal production: an overview. *Computers and Electronics in Agriculture* **123**, 10–16.
- Morota G, Ventura RV, Silva FF, Koyama M and Fernando SC (2018) Big data analytics and precision animal agriculture symposium: machine learning and data mining advance predictive big data analysis in precision animal agriculture. *Journal of Animal Science* **96**, 1540–1550.
- Nasirahmadi A, Hensel O, Edwards S and Sturm B (2017) A new approach for categorizing pig lying behaviour based on a Delaunay triangulation method. *Animal: An International Journal of Animal Bioscience* **11**, 131–139.
- Nasirahmadi A, Sturm B, Edwards S, Jeppsson K-H, Olsson A-C, Müller S and Hensel O (2019) Deep learning and machine vision approaches for posture detection of individual pigs. *Sensors* **19**, 3738.
- Neethirajan S (2020) The role of sensors, big data and machine learning in modern animal farming. *Sensing and Bio-Sensing Research* **29**, 100367.
- Neethirajan S (2021) Happy Cow or thinking Pig? WUR wolf – facial coding platform for measuring emotions in farm animals. *bioRxiv*, 2021.04.09.439122.
- Neethirajan S and Kemp B (2021) Digital livestock farming. *Sensing and Bio-Sensing Research* **32**, 100408.
- Neethirajan S, Tuteja SK, Huang S-T and Kelton D (2017) Recent advancement in biosensors technology for animal and livestock health management. *Biosensors and Bioelectronics* **98**, 398–407.
- Nie L, Berckmans D, Wang C and Li B (2020) Is continuous heart rate monitoring of livestock a dream or is it realistic? A review. *Sensors* **20**, 2291.
- Noviyanto A and Arymurthy AM (2012) Automatic cattle identification based on muzzle photo using speed-up robust features approach. *Proceedings of the 3rd European Conference of Computer Science, ECCS*, December 2-4, 2012, Paris, France, 114.
- Orihuela A, Omaña J and Ungerfeld R (2016) Heart rate patterns during courtship and mating in rams and in estrous and nonestrous ewes (Ovis aries). *Journal of Animal Science* **94**, 556–562.
- Pezzuolo A, Guarino M, Sartori L, González LA and Marinello F (2018) On-barn pig weight estimation based on body measurements by a Kinect v1 depth camera. *Computers and Electronics in Agriculture* **148**, 29–36.
- Qiao Y, Su D, Kong H, Sukkarieh S, Lomax S and Clark C (2019) Individual cattle identification using a deep learning-based framework. *IFAC-PapersOnLine* **52**, 318–323.
- Rahman A, Smith D, Little B, Ingham A, Greenwood P and Bishop-Hurley G (2018) Cattle behaviour classification from collar, halter, and ear tag sensors. *Information Processing in Agriculture* **5**, 124–133.
- Riekert M, Klein A, Adrion F, Hoffmann C and Gallmann E (2020) Automatically detecting pig position and posture by 2D camera imaging and deep learning. *Computers and Electronics in Agriculture* **174**, 105391.
- Rocha LM, Devillers N, Maldague X, Kabemba FZ, Fleuret J, Guay F and Fautitano L (2019) Validation of anatomical sites for the measurement of infrared body surface temperature variation in response to handling and transport. *Animals* **9**, 425.
- Salama A, Hassanien AE and Fahmy A (2019) Sheep identification using a hybrid deep learning and Bayesian optimization approach. *IEEE Access* **7**, 31681–31687.
- Sarwar F, Griffin A, Periasamy P, Portas K and Law J (2018) Detecting and counting sheep with a convolutional neural network. 2018 15th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS), 2018. IEEE, 1–6.
- Shah NA, Thik J, Bhatt C and Hassanien A-E (2021) A deep convolutional encoder-decoder architecture approach for sheep weight estimation. *Advances in Artificial Intelligence and Data Engineering* **1133**, 43–53.
- Shahinfar S, Kelman K and Kahn L (2019) Prediction of sheep carcass traits from early life records using machine learning. *Computers and Electronics in Agriculture* **156**, 159–177.
- Singh M, Kumar R, Tandon D, Sood P and Sharma M (2020) Artificial Intelligence and IoT based Monitoring of Poultry Health: A Review. 2020 IEEE International Conference on Communication, Networks and Satellite (Comnetsat), 2020. IEEE, 50–54.
- Slimen IB, Chniter M, Najar T and Ghram A (2019) Meta-analysis of some physiologic, metabolic and oxidative responses of sheep exposed to environmental heat stress. *Livestock Science* **229**, 179–187.
- Stewart M, Wilson M, Schaefer A, Huddart F and Sutherland M (2017) The use of infrared thermography and accelerometers for remote monitoring of dairy cow health and welfare. *Journal of Dairy Science* **100**, 3893–3901.

- Stojkov J, Weary D and Von Keyserlingk M** (2016) Nonambulatory cows: duration of recumbency and quality of nursing care affect outcome of flotation therapy. *Journal of Dairy Science* **99**, 2076–2085.
- Sutherland MA, Worth GM, Dowling SK, Lowe GL, Cave VM and Stewart M** (2020) Evaluation of infrared thermography as a non-invasive method of measuring the autonomic nervous response in sheep. *PLoS One* **15**, e0233558.
- Tahsin KN** (2016) Development of a propeller P8X 32A based wireless biosensor system for cattle health monitoring and disease detection. *British Journal of Applied Science and Technology* **18**(2), 1–14.
- Taneja M, Byabazaire J, Jalodia N, Davy A, Olariu C and Malone P** (2020) Machine learning-based fog computing assisted data-driven approach for early lameness detection in dairy cattle. *Computers and Electronics in Agriculture* **171**, 105286.
- Tian M, Guo H, Chen H, Wang Q, Long C and Ma Y** (2019) Automated pig counting using deep learning. *Computers and Electronics in Agriculture* **163**, 104840.
- Tsai Y-C, Hsu J-T, Ding S-T, Rustia DJA and Lin T-T** (2020) Assessment of dairy cow heat stress by monitoring drinking behaviour using an embedded imaging system. *Biosystems Engineering* **199**, 97–108.
- Wagner N, Antoine V, Koko J, Mialon M-M, Lardy R and Veissier I** (2020) Comparison of Machine Learning Methods to Detect Anomalies in the Activity of Dairy Cows. International Symposium on Methodologies for Intelligent Systems, 2020. Springer **12117**, 342–351.
- Wang J, Liu A and Xiao J** (2018) Video-Based Pig Recognition with Feature-Integrated Transfer Learning. Chinese Conference on Biometric Recognition, 2018. Springer, 620–631.
- Wang H, Qin J, Hou Q and Gong S** (2020) Cattle face recognition method based on parameter transfer and deep learning. Journal of Physics: Conference Series, 2020. IOP Publishing, 012054.
- Wang F-K, Shih J-Y, Juan P-H, Su Y-C and Wang Y-C** (2021a) Non-invasive cattle body temperature measurement using infrared thermography and auxiliary sensors. *Sensors* **21**, 2425.
- Wang M, Youssef A, Larsen M, Rault J-L, Berckmans D, Marchant-Forde JN, Hartung J, Bleich A, Lu M and Norton T** (2021b) Contactless video-based heart rate monitoring of a resting and an anesthetized pig. *Animals* **11**, 442.
- Wilcox J** (2020) Covid-19 sentiment and reactions among financial decision-makers in Europe. *Hanover Research*. [https://f.hubspotusercontent30.net/hubfs/2020381/~Marketing%202020/Landing%20Pages/COVID-19%20Sentiment%20and%20Reactions%20among%20Financial%20Decision%20Makers%20in%20Europe%20-%20OneStream%20-%20October%202020%20External.pdf?\\_\\_hstc=231710272.7fd81c9d080729dff81a1cd93879abaa.1601655069581.1616156525336.1616159907458.57&\\_\\_hssc=231710272.109.1616159907458&\\_\\_hsfp=53860856&hsCtaTracking=49adcd88-fd96-413c-b5a7-e72bd9087277%7C59e989fa-56ae-4b8c-bfd8-1eb1d31217d5](https://f.hubspotusercontent30.net/hubfs/2020381/~Marketing%202020/Landing%20Pages/COVID-19%20Sentiment%20and%20Reactions%20among%20Financial%20Decision%20Makers%20in%20Europe%20-%20OneStream%20-%20October%202020%20External.pdf?__hstc=231710272.7fd81c9d080729dff81a1cd93879abaa.1601655069581.1616156525336.1616159907458.57&__hssc=231710272.109.1616159907458&__hsfp=53860856&hsCtaTracking=49adcd88-fd96-413c-b5a7-e72bd9087277%7C59e989fa-56ae-4b8c-bfd8-1eb1d31217d5)
- Wu D, Wu Q, Yin X, Jiang B, Wang H, He D and Song H** (2020) Lameness detection of dairy cows based on the YOLOv3 deep learning algorithm and a relative step size characteristic vector. *Biosystems Engineering* **189**, 150–163.
- Zhang AL, Wu BP, Wuyun CT, Jiang DX, Xuan EC and Ma FY** (2018) Algorithm of sheep body dimension measurement and its applications based on image analysis. *Computers and Electronics in Agriculture* **153**, 33–45.
- Zhang M, Feng H, Luo H, Li Z and Zhang X** (2020) Comfort and health evaluation of live mutton sheep during the transportation based on wearable multi-sensor system. *Computers and Electronics in Agriculture* **176**, 105632.
- Zhang Y, Cai J, Xiao D, Li Z and Xiong B** (2019a) Real-time sow behavior detection based on deep learning. *Computers and Electronics in Agriculture* **163**, 104884.
- Zhang Z, Zhang H and Liu T** (2019b) Study on body temperature detection of pig based on infrared technology: a review. *Artificial Intelligence in Agriculture* **1**, 14–26.
- Zin TT, Phyo CN, Tin P, Hama H and Kobayashi I** (2018) Image technology-based cow identification system using deep learning. *Proceedings of the International MultiConference of Engineers and Computer Scientists* **1**, 236–247.
- Zipp KA, Barth K, Rommelfanger E and Knierim U** (2018) Responses of dams versus non-nursing cows to machine milking in terms of milk performance, behaviour and heart rate with and without additional acoustic, olfactory or manual stimulation. *Applied Animal Behaviour Science* **204**, 10–17.