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The Livestock Farming Digital Transformation: Implementation of New and Emerging Technologies Using Artificial Intelligence

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Running Title: New and Emerging Digital Technologies Applied to Livestock

Abstract

Livestock welfare assessment helps monitor animals' health status to maintain productivity, identify injuries and stress, and avoid deterioration. It has also become an important marketing strategy since increasing consumer pressure for a more humane transformation in animals' 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 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 showed 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.

Keywords: Machine learning; deep learning; animal welfare; biometrics; computer vision.

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's health, welfare, and productivity. These events have triggered and prioritised 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 have as aim 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's 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 [1-3]. However, these are apparent impractical approaches to monitor many animals in farms for continuous assessments. 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 stress levels 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 [4]. 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 physiological assessments and sensor technologies mentioned before [5].

Recent digital technological advances in sensor technology, sensor networks with The Internet of Things (IoT) connectivity, remote sensing, computer vision and artificial intelligence (AI) for agricultural and human-based applications have allowed the potential automation and integration of different animal science and animal welfare assessment approaches [6, 7]. There has been increasing research on implementing these new and emerging digital technologies and adapted to livestock monitoring, such as minimal contact sensor technology, digital collars and remote sensing [8]. Furthermore, novel analysis and modelling systems have included machine and deep learning modelling 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 [4, 9]. One of the most promising approaches is implementing AI incorporating remote sensing and machine learning modelling 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 LiDAR to predict targets, such as animal health, stress and welfare parameters. This 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 modelling techniques rather than deploying 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 and complex problems rather than concentrating on more simple and practical applications and with little deployment examples. However, the latter is a generalised 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 machine learning and 25% for AI deployment solutions, according to the Hanover Enterprise Financial Decision Making 2020 report [10]. 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 increased temperatures, droughts, and heat waves 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 behaviour, or invasive. They may involve collecting blood or urine samples to be analysed using expensive and time-consuming laboratory techniques such as enzyme-linked immunosorbent assays (ELISA) and polymerase chain reaction (PCR) [9, 11, 12]. 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) [13, 14]. 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 [1, 2]. 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 [1, 15]. Traditional techniques to assess HR may involve manual measurements using stethoscopes [16-18], 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) [19, 20], and photoplethysmography (PPG) sensors attached to the ear [21]. The heart rate parameter and variability are usually used as an indicator of environmental stress, gestation period, metabolic rate, and diagnosis of cardiovascular diseases [13, 14]. On the other hand, respiration rate (RR) is typically measured by manually counting the flank movements of animals resulting from breathing in 60 s using a chronometer [16, 18] or counting the breaths in 60 s using a stethoscope, or by attaching sensors in the nose, or thorax, which can detect breathing patterns [2]. Respiration rate can be used to indicate heat stress and respiratory diseases [16, 22, 23].

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 for cattle, sheep and pigs (Table 1).

Cattle

To assess the body temperature of cattle continuously, Chung et al. [3] 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 one 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 machine learning (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 regression ML models. On the other hand, Tahsin [24] 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. [25] 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 humiture 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 ±0.10 °C between the grountruth and the method proposed. The anemometer and humiture sensor were used to remove the frames affected by external weather factors to extract outliers.

In the case of heart rate, Zipp et al. [26] used a 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. [27] 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 also 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. [28] 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 analysed 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 0.99 for chewing data compared with manual measurements for RR y chewing and Polar sensor for HR. These latter methods may solve the contact probles and unreliavility of data quality; however, they seem to still be manual methods requiring opertaors. The authors did not proposed an automation system for measurements.

Jorquera et al. [17] 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 crush. The IRTIs were analysed 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 analysed using a customised Matlab® code previously developed for humans [29] 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 analysed 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/bias. Stewart et al. [30] 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 the 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 ThermaCam S60 camera (FLIR Systems, Wilsonville, OR, USA). The three methods showed to give similar responses with the highest average difference (0.83 ±0.57) between methods (i) and (iii). Furthermore, Lowe et al. [31] presented a similar approach but tested only in five calves. In the latter study, two methods were compared i) manual count of flank movements from an RGB video recorded using a Panasonic HCV270 camera (Panasonic, Osaka, Japan), this was made by recording the time taken for the calf to reach five breath cycles, and ii) manual count of the thermal fluctuations (colour 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 [32] used a FLIR ONE Pro infrared thermal camera to record IRTIs and RGB videos from the face of calves. The authors first measured the colour 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' nose. 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 the ones 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. [33] developed a computer vision method to assess body measurements (dimensions) of cattle using an O3D303 3D LiDAR camera to record the individual animals' side view and post-processing using filter fusion, clustering segmentation and matching techniques. Tsai et al. [34] 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 sensory for environmental measurement. This integrated module was placed on the top of the drinking troughs in a dairy farm to record drinking behaviour 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's behavioural and physiological responses using contact and contactless sensors. Giovanetti et al. [35] 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. [36] 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. Besides, 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. [37] presented a method to measure the body temperature of ewes using a button size data logger DS1921K (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. [38] 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 oestrous cycle in ewes. Sutherland et al. [39] also used an infrared thermal camera (FLIR Thermacan S60) to record videos of the left eye of ewes. These videos were analysed 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. [40] 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 heart rate 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. [41] designed a wearable collar that included two sensors to measure (i) heart rate 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 transportation of sheep. However, these studies can only monitor sentinel animals, making laborious, difficult and impractical the assessment of all animals transported.

To solve the later problem, Fuentes et al. [16] presented a contactless/non-invasive method to assess temperature, HR and RR of sheep using computer vision analysis and machine learning. The authors used a FLIR DUO PRO camera to simultaneously record RGB and infrared thermal videos of sheep. The infrared thermal videos were analysed using customised Matlab® R2020a algorithms to automatically recognise 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 analysed using customised Matlab® R2020a codes to assess HR and RR based on the PPG principle using the G colour 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 R = 0.94. This study also proposed a potential deployment system to be used for animals in transport.

For other biometric assessment, Zhang et al. [42] 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 analysed in Matlab® R2013 using the superpixel segmentation algorithm. The authors also obtained the dimension parameters manually and found a correlation 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 behavioural and physiological responses. For example, Byrd et al. [43] used a KPC-N502NUB camera (KT&C, Fairfield, NJ, USA) mounted on top of the pigs' pen to assess pig behaviour. 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. [44] assessed the lying behaviour of pigs using closed-circuit television (CCTV) with a Sony RF2938 camera above the pen. Matlab® software was used to analyse the videos using computer vision algorithms to detect the position of each pig and analyse the distance between each animal considering their axes, orientation and centroid. On the other hand, Pezzuolo et al. [45] 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 analysed 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 modelling 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. [46] used a Testo 876-1 handheld infrared thermal camera (Testo Instruments, Lenzkirch, Germany) to record images of piglets' full body. The IRSoft v3.1 software (Testo Instruments, Lenzkirch, Germany) was used to obtain the maximum and minimum skin temperature values. Rocha et al. [47] 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 pigs' 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, pain) during handling and transportation. On the other hand, Feng et al. [48] developed a computer vision and machine learning 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. [49] 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 anesthetised pig, and (ii) a Sony HDRSR5 Handycam located on a tripod above resting individual housing with a resting pig. Matlab® was used to analyse the videos by selecting and cropping the (i) neck for the first setup and (ii) abdomen, neck and front leg for the dual setup. Authors used the PPG principle using the three colour 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. [50] also developed a method using anesthetised pigs; they used a long wave infrared VarioCam HD head 820 S/30 (InfraTecGmbH, Dresden, Germany) to assess HR and RR. The videos were analysed 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 a determination coefficient $R^2 = 0.96$ for HR compared to the ECG method and $R^2 = 0.97$ for RR compared to ventilator data. Jorquera-Chavez et al. [51] 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 [17] 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. [52], 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.

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	References
			Cattle				
Dairy cows	Body temperature	Implanted RFID biosensor and Machine learning	Vaginal temperature (probe)	3	RMSE = 0.08	First steps for precision agriculture methods	3
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	24
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	25
German Holstein cows	HR HRV	Wearable sensors	None	40	Not reported	Tested impact of different stimulation methods	26
Dairy calves	HR	Wearable sensors	None	69	Not reported	Behavioural and stress response	27
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 optimised cattle treatment	28
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	17
Dairy cows	RR	Computer vision Infrared thermal and RGB videos	Manual count	15	Mean difference Manual vs RGB video: -0.01 ±0.87 Manual vs infrared videos: 0.83 ±0.57	Monitoring of health and welfare	30

Calves	RR	Contactless biometrics Computer vision Infrared thermal images	Manual count from RGB videos	5	$R^2 = 0.93$	Monitoring of health and welfare	31
Japanese Black Calves	RR	Contactless biometrics Computer vision Infrared thermal images Deep learning	Manual count	5	$R^2 = 0.91$	Monitoring health	32
Qinchuan cattle	Body measurements (dimensions)	Contactless biometrics Computer vision RGB images	Manual measurements	3	2 mm	Contactless body measurements of large livestock	33
Dairy cows	Drinking behaviour	Integrated sensor module Computer vision Deep learning	None	25	Not reported	Automatic and quantitative assessment of drinking behaviour as a measure of heat stress	34
			Sheep				
Dairy sheep	Behaviour actrivities	Wireless system Wearable sensors RGB videos	Manual assessment	3	93%	Behaviour assessment	35
Ewes	Behaviour actrivities	Wearable sensors RGB videos Machine learning	Manual assessment	6	85%	Assessment of sheep activity prevous to methane measurements Assessment of temporal grazing patterns	36
Ewes	Body temperature	Wearable sensor	None	15	Not reported	Measurement of temperature changes in lambing period	37
Ewes	Surface temperature of different areas (anus, vulva, muzzle, eyes)	Contactless biometrics Computer visión Infrared termal images	Rectal and vaginal temperature	20	Not reported	Assessment of temperature during oestrous cycle Reproductive managment	38

Ewes	Eye temperature HR HRV	Computer visión Infrared termal images Wearable sensors	None	20	Not reported	Assessment of autonomic nervous system responses	[39]
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	[40]
Mutton sheep	HR Oxygen saturation Body temperature	Wearable sensors	None	Not reported	Not reported	Disgnose survival status during transportation	[41]
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	[16]
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	[42]
			Pigs				
Pigs	Behaviour	Contactless biometrics Computer vision	None	10 pigs /2 replicatio ns	Not reported	Assessment of heat stress	[43]
Pigs	Lying behaviour	Contactless biometrics Computer vision	Not reported	88	96%	Welfare assessment	[44]
Pigs	Body measurements (dimensions) Weight estimation	Contactless biometrics Computer vision	Manual measurments	78	R^2 > 0.95 to predict weight	Estimate pigs' weight during weaning period	[45]
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	[46]

Sows	Rectal temperature	Contactless biometrics Computer vision Infrared thermal images Machine learning	Rectal temperature (mercury thermometer)	99	R^2 = 0.80	Welfare assessment	[48]
Pigs	HR	Contactless biometrics Computer vision	Electrocardiogram	2	78% (Green colour channel)	Real-time monitoring of health and welfare	[49]
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	[50]
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	[51]
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	[52]

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

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, behaviour, 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; some may be unreliable and easily hacked or interchanged. Furthermore, they require human labour for their maintenance, making them time-consuming and prone to human error and may lead to swapping tags [53-56]. 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 [57] and cows based on different features such as the face [53, 58], muzzle [55], body patterns [54], iris recognition [59], or retinal patterns [56].

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 analysed 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 recognised, a deep learning model is developed to identify each cow [55, 60-64]. Face recognition methods using different techniques such as local binary pattern algorithms [58] and CNN have been proposed for specific cattle breeds with different colours and patterns, such as Simmental [65], Holstein, Guernseys, and Ayrshires, among others [53, 66]; 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 is the cattle recognition from the side [67], from behind [68], different angles [69], or from the top [70]. The latter was proposed to identify and recognise Holstein and Friesian cattle using an unmanned areal vehicle (UAV) [70-73]. Bhole et al. [67] 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) [74] and face recognition using classification methods such as machine or deep learning. Salama *et al.* [75] developed a deep learning model based on CNN and Bayesian optimisation and obtained an identification accuracy of 98%. Corkery *et al.* [76] proposed a method based on independent components analysis and the InfoMax algorithm to identify the specific components from the normalised images of the sheep's 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 top of the pens. Hansen *et al.* [77] developed a face recognition method using CNN with high accuracy (97%). Marsot *et al.* [78] 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.* [79] 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%. Huan *et al.* [80] tested a Weber texture local descriptor (WTLD) identification method with different masks to detect and recognise 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. [81] based their automatic identification method on computer vision to recognise marked pigs within a pen using the Fourier algorithm for patterns description and Euclidean distance; this technique resulted in an 89% accuracy.

Machine and deep learning application in livestock to address complex problems

This section concentrates specifically on the research on AI application using machine learning and deep learning modelling techniques on livestock, specifically for cattle, sheep and pigs. One of the latest researches has been focused on the use of AI to identify farm animals' emotional response, including pigs and cattle [82]. 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 since they require either destructive or invasive methods to obtain data.

Cattle

A simple AI approach was proposed using historical data (four years) with almost ubiquitous sensor technology in livestock farms, such as meteorological weather stations with daily temperature and relative humidity [83]. 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 modelling. 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 AI applications of AI in cattle, in this case, would be whether it is worth the significant extra investment in hardware and machine learning modelling 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 machine learning modelling approaches [84, 85]. 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 [11], such as collars, halter and ear tag sensors [86], to detect physiological changes, behaviour and other anomalies [87].

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 [88], which makes possible the extraction of physiological information from those specific regions using machine learning modelling, such as heart rate from the eye section or exposed skin (e.g. ears or muzzle) and respiration rate from the muzzle section. These animal features should be recognised in a video to extract enough information to obtain physiological parameters that currently require 4-8 seconds (e.g., heart rate and respiration rate) for the signal to stabilise and get meaningful data. Hence, the AI implementation steps should consider animal recognition, specific feature recognition and tracking and extraction of physiological parameters using machine learning. This may also be integrated as a whole system along with automatic animal identification using face recognition and deep learning as proposed in Figure 1.

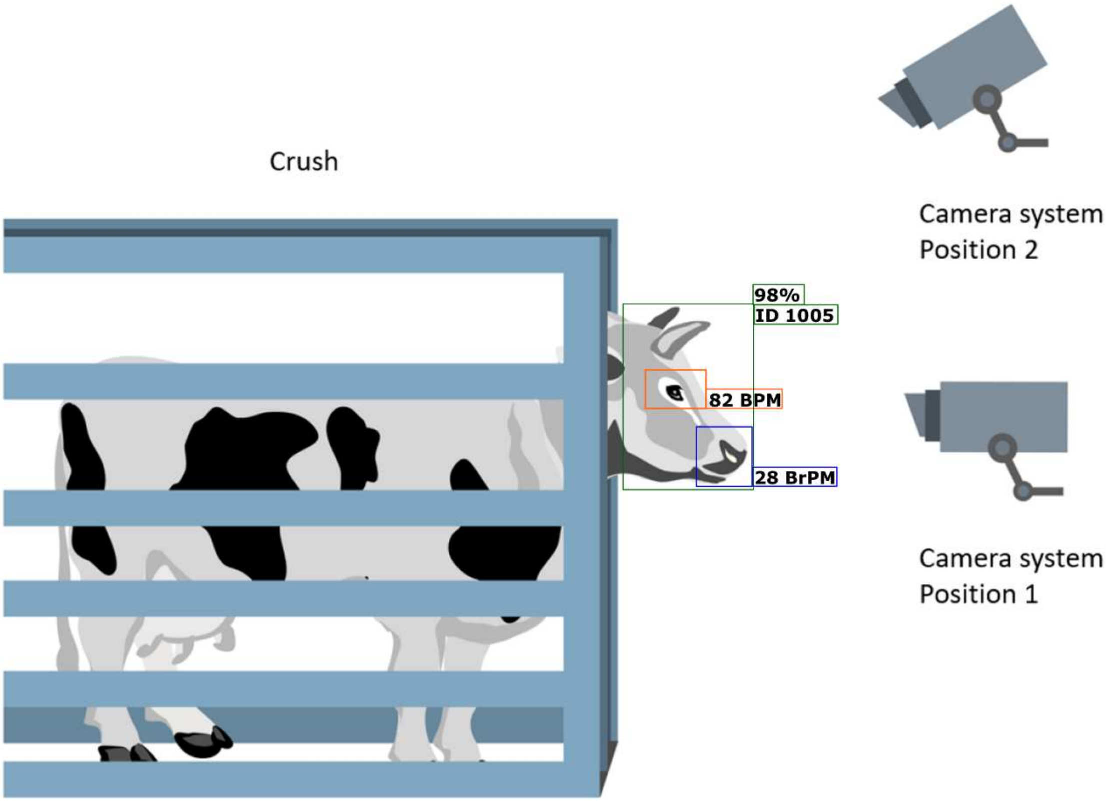

Figure 1. Proposed artificial intelligence system to assess dairy cows integrated system for face recognition, animal identification (green box) and biometrics such as heart rate in beats per minute (BPM; orange box) and respiration rate in breaths per minute (BrPM; green box). The percentage in the green box represents the certainty of identification.

Integration of UAV, computer vision algorithms and CNN have been attempted for the recognition of cattle from the air [89]. 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 machine learning approaches for sheep using electronic collars and ear sensors as input data and supervised selecting several behaviour parameters as targets with a reported accuracy of <90% for both methods [90]. Some predictive approaches from existing data have been attempted to assess carcass traits from early-life animal records [91] using supervised and unsupervised regression machine learning 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 [92], 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 [93]. Following this approach, additional physiological parameters, such as heart rate, body temperature and respiration rate, can be extracted from individual sheep non-invasively [16]. 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 reported, which can be used to assess further animal welfare [94].

Pigs

Some simple machine learning applications have been implemented to predict water usage in pig farms using regression machine learning algorithms [95]. However, this study reported a maximum determination coefficient of R2 = 0.42 for regression tree algorithms, which could be related to poor parameter engineering, since only temperature and relative humidity was used.

Automatic pig counting [96], pig posture detection [97, 98], mounting [99] and sow behaviour [100], localisation and tracking [101], aggressive behaviour [102] 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 recognised, such as biometrics including heart rate and respiration rate extracted for other animals, such as sheep mentioned before [16] and cattle identification [73] 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 to 7 days of infection) of respiratory diseases in pigs using deep learning approaches [103]. Other computer vision approaches using visible and infrared thermal imagery analysis without machine learning approaches also delivered an acceptable assessment of respiratory diseases in pigs [51].

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, has identified as a priority.

It is difficult to assess the applicability or deployment options from different research done so far on livestock, which have applied biometrics and AI since 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, since circumstances in real life scenarios change in 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 much of the AI developments and modelling 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 machine learning approaches. Academic exercises based on AI modelling for its sake only rarely reach pilot programs and applications to the real world. 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 modelling, development and deployment strategies should have a multidisciplinary team with constant communication during the model development and deployment stages; or what could be a better approach, but very rare nowadays is to have an expert on animal science, data analysis and AI dealing with business companies. This could change soon through specialised Agriculture, Animal Science and Veterinary degrees in which data analysis, machine learning and AI is 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.

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