Available online at www.worldscientificnews.com

World Scientific News

An International Scientific Journal

WSN 181 (2023) 68-98 EISSN 2392-2192

A comprehensive review of smart animal husbandry: Its data, applications, techniques, challenges and opportunities

Rotimi-Williams Bello[1,*], **Ahmad Sufril Azlan Mohamed**[2], **Abdullah Zawawi Talib**[2]

[1]Department of Mathematics/Computer Science, University of Africa, 561101 Sagbama, Bayelsa, Nigeria

[2]School of Computer Sciences, Universiti Sains Malaysia, 11800 Pulau Pinang, Malaysia

*E-mail address: sirbrw@yahoo.com

ABSTRACT

Smart systems have momentously changed the traditional methods of animal husbandry as a practice of raising livestock in the domain of agriculture. Productive and competitive animal husbandry are made possible with the use of modern technologies like machine learning models. The modern technologies enable the collection of extensive amount of smart animal husbandry data which can be employed for day-by-day animal measures such as morphological measures, physiological measures, phenological measures and other related measures. This paper dwells on three most important aspects of modern-day smart animal husbandry. First, the paper emphasizes animal measures as big data. Second, it presents all-inclusive practical applications of animal measures in smart animal husbandry. Third, it discusses mainstream machine learning techniques that are employed in smart animal husbandry analysis. By so doing, some of the prevailing challenges and prospective opportunities are identified. To the best of our knowledge, there is no existing paper that has reviewed smart animal husbandry as reviewed in this paper considering the applications and techniques that are involved in it in addition to the prevailing challenges and prospective opportunities that are comprehensively identified. The varieties of animal considered in this survey are cattle, goats and pigs.

***Keywords*:** Agriculture, Animal measures, Deep learning, Sensor, Smart animal husbandry

(Received 23 April 2023; Accepted 20 May 2023; Date of Publication 22 May 2023)

1. INTRODUCTION

Animal husbandry as agricultural practice of raising livestock in the domain of agriculture is a strenuous task that involves so many challenges. The introduction of technology to farming is imperative for mitigating these challenges for animal traceability, health information, and performance recording (Gebbers and Adamchuk, 2010). Also, as the world keeps experiencing increase in population growth , there is a need to expand production of food (meat) by ensuring good welfare of farm animals in order to commensurate with the population growth (FAO, 2009). Farm animals' welfare will ensure availability of nutritional food of high quality all over the world. However, unguarded expansion of farm animals and improper monitoring of their activities can pose a challenge to their productivity. Therefore, there is a need to protect and understand the changeable agricultural systems by employing farming procedures that are sustainable and continuously monitoring the different physical happenings. Furthermore, the employment of technologies such as those applicable to information dissemination and communication (Bello and Moradeyo, 2019; Bello and Abubakar, 2019; Kamilaris et al., 2016), big data analysis (Kamilaris et al., 2017) and management of both small and large scale animal husbandry will help in protecting and understand the changeable agricultural systems. In some settings, larger scale study is made possible by the use of drones (Xu et al., 2020), thereby enabling wider coverage of the agricultural settings.

Being a non-lethal method of capturing visual data, there are so many other advantages of applying drones in agriculture (Xu et al., 2020),. Most of the data that are remotely collected comprise of images which sometimes depict agricultural settings that could proffer solution to many agricultural challenges (Liaghat and Balasundram, 2010). Therefore, it is widely accepted that imaging analysis forms an important part of research area in the domain of agriculture with techniques of smart data analysis being employed for the identification and classification of images (Saxena and Armstrong, 2014). From the existing methods employed for remote data collection, unmanned aerial vehicle (UAV) is one of the most common methods (Shao et al., 2020). Quadcopter vision system (QVS) is being employed as a drone in a newly but rising magnitude (Xu et al., 2020). Machine learning techniques such as regression, classification, clustering, dimensionality reduction, ensemble methods, word embeddings, transfer learning, reinforcement learning, natural language processing, and neural networks among others are popular techniques employed for image analyses (Saxena and Armstrong, 2014).

Smart animal husbandry has what it takes when it comes to individual animal analysis with sensors-acquired enormous amounts of data and perception tools smartly occupying its core (Qiao et al., 2021a). The aim of smart animal husbandry is to address the stagnation in animal husbandry productivity caused by mixed traditional practice, instability in climate, and environmental and socio-economic phenomena. To the best of our knowledge, there is no existing paper that has reviewed smart animal husbandry as reviewed in this paper considering the applications and techniques that are involved in it in addition to the prevailing challenges and prospective opportunities that are comprehensively identified. Therefore, the main goal of this paper is to reveal and bridge the gap in the existing works. Fig. 1 summarizes the intelligent perception for smart animal husbandry. The contributions of the paper are as follows:

- Insightful overview of smart animal husbandry data.
- All-inclusive practical applications of smart animal husbandry data
- Comprehensive discussion of the most popularly employed mainstream machine learning techniques in smart animal husbandry.

- Identified prevailing challenges and prospective opportunities in smart animal husbandry.

The remaining of this paper is structured as follows: Section 2 presents the methodology. Section 3 presents animal measures as smart animal husbandry data. Section 4 presents all-inclusive practical applications of smart animal husbandry data. Section 5 presents comprehensive discussion of the most popularly employed mainstream machine learning techniques in smart animal husbandry. Section 6 discusses the smart animal husbandry challenges and the opportunities therein for future research. Section 7 concludes the review.

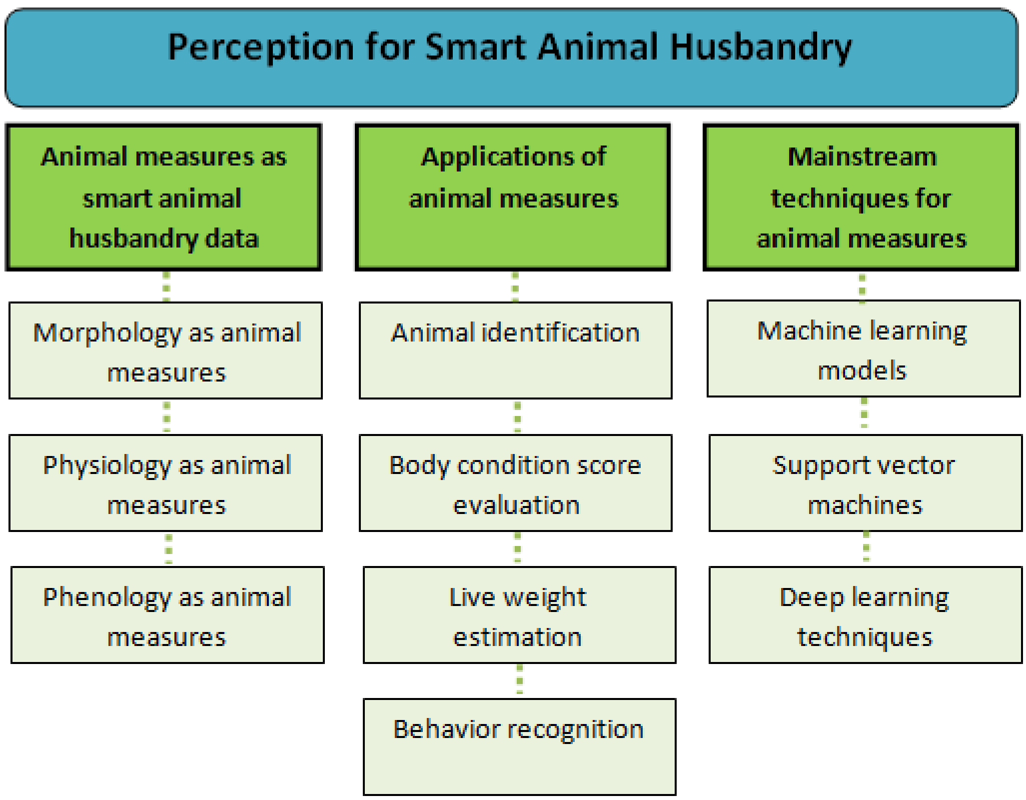

Fig. 1. An overview of perception for smart animal husbandry

2. METHODOLOGY

The methods of collection, review and detailed analysis of related works that formed the bulk of the approach employed in this paper are described in this section. The first task was to search for relevant papers from top-notch and cutting edge conference proceedings and journals' repositories using indexing words. We carefully ensure that our query words relate to animal husbandry data and machine learning techniques, and the entire review was then base on the retrieved papers. After sourcing for the materials using the information retrieval methods, the next task was to achieve the objectives of our review by answering some research questions applicable to the retrieved papers among which are:

(a) How can the papers address the existing questions on smart animal husbandry data?
(b) What are the applications of animal measures in smart animal husbandry?
(c) What are the mainstream techniques used in (b)?
(d) What are the prevailing challenges and opportunities therein for future research and more effective smart animal husbandry?

The research questions raised in this paper were appropriately addressed and the findings are presented in the subsequent sections.

3. ANIMAL MEASURES AS SMART ANIMAL HUSBANDRY DATA

Smart animal husbandry involves data which are most often acquired by interested researchers either as source of information valuable enough for industrial application or for advancing the course of research. Information such as animal identification, body condition score, weight estimation, lameness detection, behavior analysis, food conservation, and energy efficiency are few of the applications of the smart animal husbandry data. To have a clear perception for the smart animal husbandry data, and based on the existing data repositories, animal measures were classified into morphological measures, physiological measures, and phenological measures with examples for each measures in bullets as shown in Fig. 2.

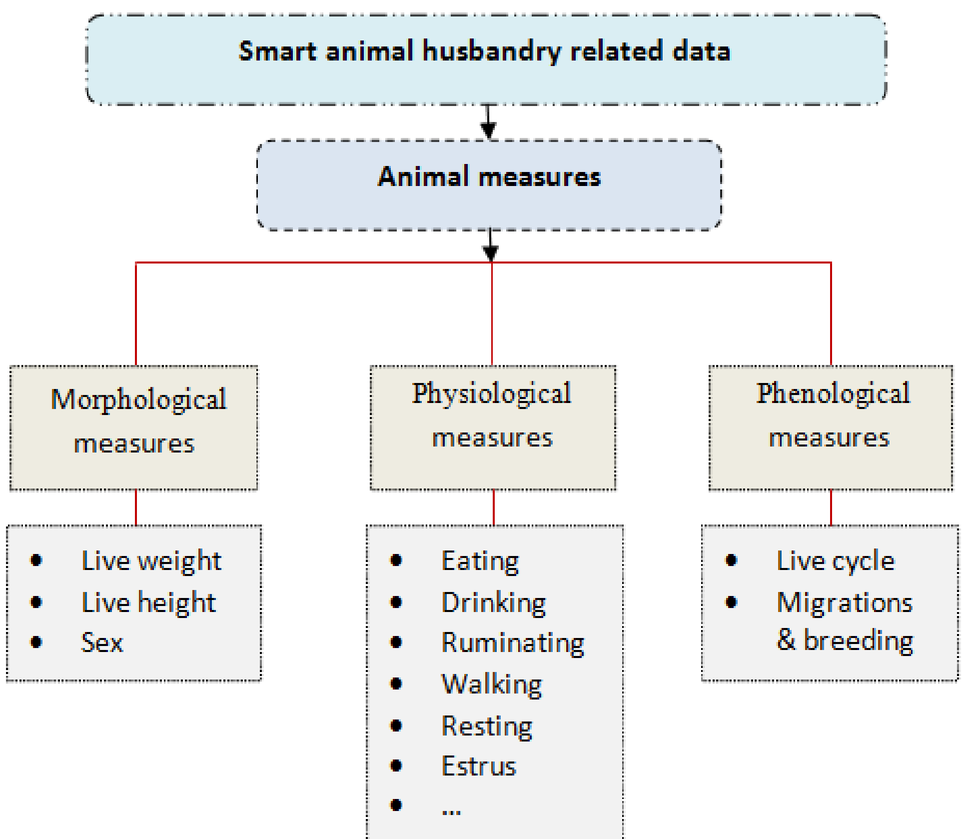

Fig. 2. An overview of animal measures as smart animal husbandry data

The three forms in which animal measures could be acquired are in form of morphological data, physiological data and phenological data. To be highly productive, body measurements which include body condition score and weight are essential in animal husbandry. Evaluating and estimating the body condition score and weight is important for the performance evaluation of the animal's productive efficiency and competitiveness. For instance, low body condition score and loss in weight are both indicators of lack of welfare, which is supposed to aid or promote well-being of the animal.

Availability of food and water is important in animal husbandry, with the necessary animal measures in place, it will be very easy to regulate animal ration equitably. Ruminant animal daily behavioral activities such as eating, drinking, ruminating, walking, resting, and estrus are all indicators of physiological measures which serve as source of information to farmers for decision making. Phenologically and morphologically, crossbreeding, which is the act of mixing different species or varieties of animals and thus producing hybrids is another contributory aspect of animal measures in animal husbandry that could be used to improve animal health status and productivity. Animal height and weight, number of offspring per birth are major factors that determine crossbreeding as phenological and morphological data for predicting high future growth and productivity.

4. APPLICATIONS OF ANIMAL MEASURES

In animal husbandry, individual animal recognition is essential for both animal monitoring and treatments. Animal measures have been applied to animal monitoring as well as behavior analysis of animals with respect to feeding and drinking habits. Modern state-of-the-machine learning models are being applied for the management of animal husbandry. Evidence to support this assertion is the recent proliferation of published articles on new technologies applied to animal farming thereby raising more research awareness (Caria et al., 2017). Monitoring of animals through biometric and visual methods assists in maintaining their quality life. Live weight estimation and body condition score evaluation are other applications of the models (Fig. 1). Bello et al. (2020a) employed image-based technique for cattle recognition using the cattle body patterns. In Bello et al. (2021a) and Bello et al. (2020b), deep belief network and deep learning models were applied on cattle nose image patterns for cattle recognition. Deep learning-based counting systems have been employed for automatic identification, counting, and description of wild animals in camera-trap images in order to have first hand information about their activities (Norouzzadeh et al., 2018). Norouzzadeh et al. (2018) trained deep convolutional neural networks to extract the needed data from camera-trap images automatically.

By using state-of-the-art data mining techniques, there is possibility of achieving all the goals of animal husbandry for the overall benefit of livestock industry. Animal breeders apply crossbreeding as animal measures in their animal breeding to produce breeds that are productive and that can stand any health challenges. Morphological and phenological details about individual animal may be of interest to the researchers such as sex of offspring at birth, number of offspring per birth, immunity to disease and unfavorable conditions. These and many more are what animal husbandry farmers especially, dairy and beef farmers desire to have better knowledge of knowing, in order to accurately predict the most favorable conditions for their animals to produce more. Although, it is herculean task to apply the animal measures techniques to smart animal husbandry, reason is that, sometimes, there is need to integrate data from two different sources. Xu et al. (2020) for instance, in counting cattle in feedlots and open field employed ground-truth image data in addition to target image data. It is not out of place to re-employ previous profitable data to forecast future produce (Alwis et al., 2022). This arrangement gives solid yield assurance provided uncontrollable influencing factors such as drought season that can thwart the predictions are taking into consideration. Animal husbandry farmers most affected by the drought hope that there may yet be sufficient rain throughout the year either natural or man-made because water availability is an important factor for higher yield in animal husbandry as drought can as well make the animal conditions and performance to degenerate. More accurate predictions that are reliable can be achieved by transferring and incorporating already pre-trained data and models into the new models (Xu et al., 2020).

4. 1. Animal identification

The varieties of animal in the animal husbandry studied in this paper are cattle, goat and pig. Identification of individual animals facilitates the management level of individuals. Applications of any of the animal measures aids the identification and recognition of individual animals, whereby tracking and classification of applicable individual features over time is made possible (Su et al., 2022). Animal measures application for individual animals identification involves various techniques, most of which range from traditional to mainstream methods as shown in Fig. 3. Fig. 3 illustrates the farm animal identification methods. This is further presented in Table 1 to show the existing research work on the identification of varieties of animal in the animal husbandry studied in this paper.

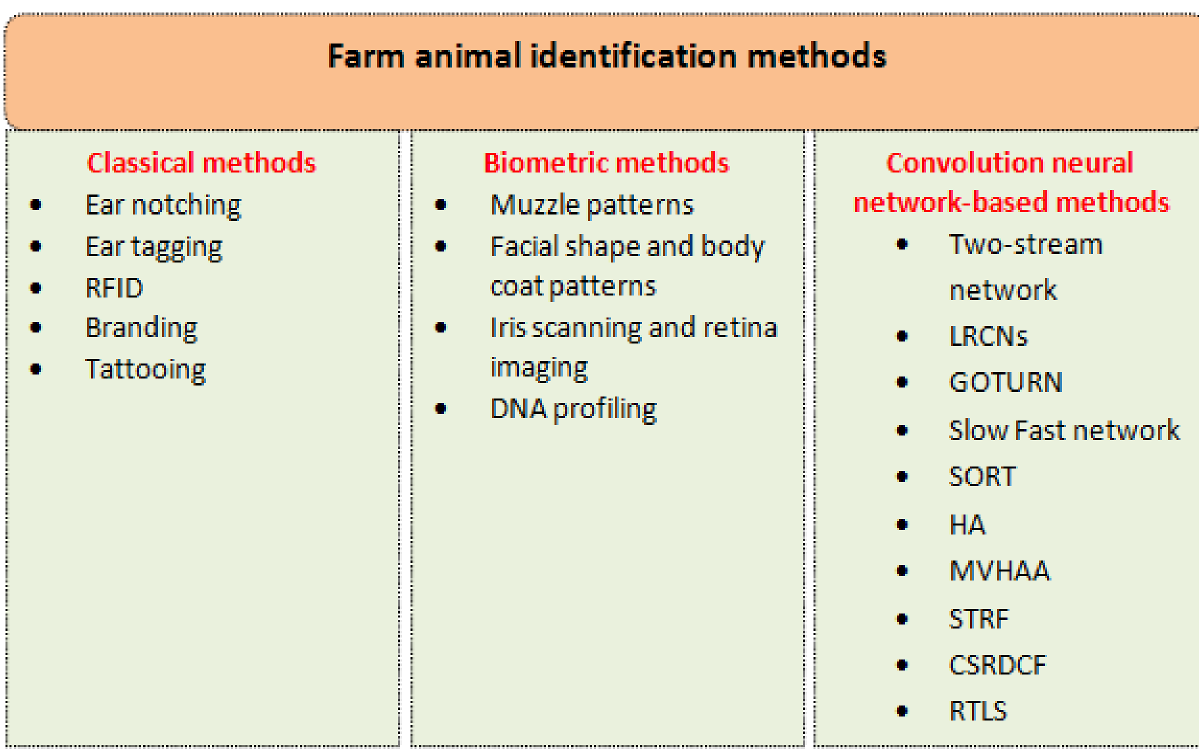

Fig. 3. Farm animal identification methods with examples for each method in bullets

4. 1. 1. Classical methods

Farm animal identification using classical methods mostly involves the traditional approach of applying the methods. Commonly used methods are ear notching method, ear tagging method, Radio Frequency Identification (RFID) method, branding method, and tattooing method.

4. 1. 1. 1. Ear notching method

Ear notching is a conventionally organized method that is commonly practiced by animal breeders for pig identification in which individual pig's identity is based on their order of birth within the obtainable breeding for lasting identification provided the method is applied correctly. Litter number (popularly used for identification of offspring of a multiparous mammal at one birth) is a number that is notched on the breeds' right ear otherwise known as litter ear, and the breeds are notched within the litter on the breeds' left ear otherwise known as individual breeds' ear. Within the same litter, different breeds' numbers are assigned to breeds but with the same litter number. This method is applicable for pig breeds identification when there are many breeds given birth to at the same time in typical pig farming.

4. 1. 1. 2 Ear tagging method

Different methods have been employed in tagging of farm animals such as cattle, goat, sheep, and pig over many decades ago. Wearing of collars on farm animals originated from the Akkadian texts written more than five thousand years ago (Blancou, 2001). Important details that facilitate animal identification are written on the medallion and fastened to collars for easy identification of the affected animals. Moreover, earrings were applied on farm animals in Persia for easy identification of animals with same morphological structure (Blancou, 2001).

Different methods exist on how tags can be attached on farm animals; neck-chain is one of the methods (Neary and Yager, 2002) followed by piercing method. To apply piercing method in attaching tags on the farm animals, the animals' ears especially that of cattle are pierced in-between the cartilage ribs making the front and rear identification so conspicuous. As relatively cheap as tag is couple with its apparent readability, the process for achieving it could be hurtful and harmful.

An indelible ear tagging devices that is visible are usually used for cattle identification. The indelible ear-tagging method employs a plastic-based label that is visible enough and hanged on the punctured ear of the breeds with a number written on it (Bello and Abubakar, 2019). Notable challenges militating against using ear tagging method for cattle identification is the cost of applying it in monitoring large herd and the manual means of attaching the devices to individual animals.

4. 1. 1. 3. Radio Frequency Identification (RFID) method

RFID is a widely employed method for electronic animal identification and traceability particularly for ruminants like cattle, goats and sheep. RFID mechanism is such that a communication is initiated between the RFID and a reader through a microchip with a small transmitter radio and antenna that are embedded in the RFID. RFID technology can be applied in different ways among which are ear tags, neck collars (common method), ruminal boluses, and microchip implants.

The technology of RFID for cattle's ear tags is an ear embedded technology in form of a number ear tag. The method of applying neck collars which are similar to neck chains is by using electronic tagging as an alternative to number tag (Bello et al., 2020c; Bello and Abubakar, 2020; Bello and Moradeyo, 2019; Bello et al., 2020d). To apply ruminal boluses on cattle, a Balling gun is employed by keeping hold of the ruminal boluses in the cattle fore-stomach (Ghirardi et al., 2006). A scanner is needed to read the microchip and interpret the radio signal as a numerical code regardless of the RFID technologies employed, and ensure the generation of recorded information about individual cattle from the models designed for herd management (Neary and Yager, 2002). No visual readings is required with RFID technology because there is provision of unique identification codes for individuals, and the signal strength possesses by the RFID technology has the power to penetrate walls and get read by the scanner, nevertheless, the installation of RFID technology involves highly skilled professionals and at the same time costly to set it up with no assurance of getting the transponders kept.

4. 1. 1. 4. Branding

The ancient Egyptians were the first set of people in history to use hot iron branding as animal identification method to identify cattle. To get hot iron-based branding, the branding irons are subjected to fire to get them heated till they become red hot enough for branding which can be applied to the hair on the body of the animal to kill the cells that are responsible for the growth of the hair follicle thereby achieving permanent markings. Freeze branding is another type of branding that resembles hot branding but differs in method. In freeze branding, either dry ice or liquid nitrogen and alcohol are used to chill the branding irons instead of using the iron branding method.

Reason for applying this method to the animal's hide is to ensure the protection of the cells that are responsible for growing the hair while the cells that color the hair is being killed by the chilled iron. This method yields permanent branding marking from the growth of either colorless or white hair (Neary and Yager, 2002). Another method of identifying animals in animal farm is by paint branding. Paint branding is a conspicuous temporary identification method that its method of application is similar to freeze and hot iron branding methods. The main difference between the paint branding method and the two other branding methods is that paint brands are subjected to paint soaked burlap sack instead of allowing them to undergo the procedures that the two other branding methods undergo prior to pressing them on the animals' body (Neary and Yager, 2002).

4. 1. 1. 5. Tattooing

Tattooing is a common method for staining skin permanently with indelible ink. This method is applied to animal body for their permanent identification by engraving alphanumeric characters into the skin of the animal. Most ruminant animals like cattle have their tattoos engraved in their ear just above the first cartilage rib to prevent interference of ear tags. Application of tattoo to animals like cattle is by using tattoo tools (Neary and Yager, 2002) for injury-free tattoo punctures on the animal. The resultant carves, cut, or etch as a consequence of the punctures is treated with alcohol, and a relatively amount of ink is rubbed into the punctures with the tattoo pressed on; leaving permanent and conspicuous tattoo at the end of the tattooing process. Technology advancement is gradually changing the conventional method of applying tattoo on animals, thereby improving the procedures.

4. 1. 2. Biometric and visual methods

Different biometric methods exist for identifying animals such as muzzle patterns-based methods (Bello et al., 2020b), facial shape imaging (Cai and Li, 2013), body coat pattern imaging (Bello et al., 2020a), iris scanning and retinal imaging (Marchant, 2002), and DNA profiling (Marchant, 2002). The unique physical characteristics such as muzzle patterns, facial shape, body coat patterns, and iris and retina vascular patterns together with DNA profiling possess by individual animals can serve as biometric authentication features through the application of computer vision-based methods for a lasting solution to problems of animal identification (Andrew et al., 2017).

4. 1. 2. 1. Muzzle pattern-based methods

Muzzle patterns are unalterable and permanent identification method commonly employed in animal identification (Bello et al., 2020b). Going by the similarity between muzzle patterns and human fingerprints couple with the established fact of six identifiable matching lines or dots that differentiate human fingerprints which is also an attribute possess by muzzle patterns, it simply means that there can never be two identical muzzle patterns from different animals. Petersen (1922) has carried out an advanced research work on this identification method. By using headlocks, farm animals like cattle whose individual nose prints are needed for identification procedure are restrained and have their nose cleaned and dried before applying small amount of ink on it. The applied ink facilitates a carbon copy of the nose on a firmly-held index card pressed on the ink print (Neary and Yager, 2002). This identification method is not painful, neither is it hurtful nor harmful. On the contrary, it is a unique method of identifying individual animals although; a great effort is required to restrain the affected individual animals to get their nose prints. Furthermore, prints are uneconomical and inefficient because, they can neither be reposited nor swiftly read (Marchant, 2002). However, nowadays, muzzle images used for pattern recognition are being collected using digital cameras with feature descriptors such as Local Binary Patterns (LBP), and Speeded-Up Robust Features (SURF) or Scale-Invariant Feature Transform (SIFT) (Kusakunniran et al., 2018; Ahmed et al., 2015; Kumar et al., 2017). Furthermore, deep learning techniques have been used to identify muzzle patterns of individual cattle (Kumar and Singh, 2017; Kumar et al., 2018; Kumar and Singh, 2020; Mahmoud and Hadad, 2015) with great recognition accuracy. Ahmed et al. (2015) presented an invariant biometric-based identification system based on muzzle print images for cattle identification. The system employs Speeded Up Robust Feature (SURF) features extraction technique and Support Vector Machines (SVMs) classifiers. Although the experiment performed on 217 muzzle print images has shown that the system has achieved an excellent identification rate, it does not work well in handling automated recognition.

4. 1. 2. 2. Facial shape and body coat pattern based approaches

Zin et al. (2018) employed a computer vision system with body pattern technique to recognize individual Holstein cattle in natural light. Their experiment produced great reliable results for the cattle identification. Cai and Li , 2013) employed local binary pattern descriptor with facial imaging using machine learning models for cattle face recognition, which produced substantial recognition accuracy in identifying individual cattle. Extraction of facial and body coat features of animals for their individual identification has been made possible by machine learning methods (Arslan et al., 2014). Bello et al. (2020a) in order to identify individual cow and alleviate the herculean tasks involved in the identification process especially with illumination variation, proposed an image processing system for processing the image of the cow's body patterns. The proposed system classifies the output of the processed input image under certain categories. Each of the one thousand body pattern images they acquired from ten species of cow was trained and tested using series of convolution layers in convolutional neural network for the classification of the pattern images with probabilistic values set between 0 and 1. Their proposed system achieved 92.59% and 89.95% performance accuracy on trained and tested data respectively. To achieve absolute identification results, great consideration should be given to the methods employed for the selection and feature extraction of facial and body coat patterns of the animal.

4. 1. 2. 3. Iris scanning and retina imaging

The technology of iris scanning which is by using a video-based eye image snapshot has been practically employed for animal identification. The technology is by extracting the iris pattern of the animal and encodes it for the animal recognition. According to (Marchant, 2002), it is not advisable to perform iris scanning operation on young animals until they attain maturity because, the unique characteristic features of the animal's iris pattern can be affected by injury and infection at early age. On the other hand, the technology of retinal imaging which is by using the unique and inflexible pattern of retinal vascular present in the animal at birth has been applied for individual animal identification using a manually handled computer with an ocular fundus digital video camera linked to GPS (Global Positioning Satellite) receiver for automatic encoding of details such as the location where the retina was captured including the date and time it was captured (Marchant, 2002). These unique and unalterable biometrics methods are improvement on those identification methods that cause pain, injury, and infection (Allen et al., 2008). Iris patterns were incorporated with the 2D Complex Wavelet Transform (2D-CWT) for individual cattle identification, which achieved 98.33% accuracy (Lu et al. 2014). However, the difficulty involves in capturing the iris and retina images from moving cattle limits the applicability of these methods.

4. 1. 2. 4. DNA Profiling

The technique of DNA profiling was employed by Marchant (2002) in pedigree breeding of animals to ascertain/secure their (1) identification, (2) source verification, and (3) parentage. The use of single nucleotide polymorphism (SNP) fingerprint was required by DNA profiling for the individual animal recognition. Electronic systems for identifying animal were studied by Evans and Van Eenennaam (2005), and their findings revealed that there is less than one in a trillion possibilities that two individual animals will in happenstance have identical 30-SNP loci genotypes.

4. 1. 3. Convolution neural network (CNN)-based methods

The widely acceptability of convolution neural network-based methods with ability to achieve accurate result-oriented image feature extraction and representation has continue to grow in the field of vision and image processing (Bello et al., 2021b; Bello et al., 2021c; Bello et al., 2021d). Although, these methods have been widely applied for animal identification purposes such as cattle without the need for pre-specifying any features (Kumar et al., 2018) but, the application of CNN-based methods in monitoring the activities of animals in animal farming is still not widespread (Li et al., 2021). The two-stream network by Simonyan and Zisserman (2014) is one of the tracking models proposed in literature for tracking moving objects. It uses several layers of convolutional networks and optical flow convolutional networks to capture from still frames relevant information on object, and tracks the object movement between frames. Shortly after two-stream network was proposed, Long-term Recurrent Convolutional Networks (LRCNs) were developed. LRCNs (Donahue et al., 2015) generally comprise several CNNs, namely Inception modules, ResNet, VGG and Xception for extracting spatial and temporal features.

LRCN was the most applied tracking model because its architectures are reasonable for tracking performance. Generic Object Tracking Using Regression Networks (GOTURN) (Held et al., 2016) is another existent lightweight network object tracking model that achieves 100 fps (frames per second) for object tracking. GOTURN was initially trained with generic objects filled datasets. ROIs on the frames are used as input data into the trained network during the testing, whereby continuous prediction of target's location is made possible. The Slow Fast network (Feichtenhofer et al., 2019) on the other hand tracks objects using two streams of frames, namely slow pathway and high pathway. Simple Online and Real-time Tracking (SORT), Hungarian Algorithm (HA), Munkres Variant of the Hungarian Assignment Algorithm (MVHAA), Spatial-aware Temporal Response Filter (STRF) and Channel and Spatial Reliability Discriminative Correlation Filter tracker (CSRDCF) are other existing tracking algorithms tailored to animal monitoring (Alameer et al., 2020; Chen et al., 2020; Cowton et al., 2019; Zhang et al., 2019).

These algorithms were utilized by object detection models such as Faster R-CNN, FCN, SSD, VGG and YOLO for the detection and tracking of animals in images using their geometric features in continuous frames (Li et al., 2021). To provide a method that is reliable and efficient for monitoring the behavioral activity in cows, Ren et al. (2021) presented a tracking system embedded with ultra-wideband technology; this is similar to the work of Salau et al. (2019). They employed computer vision module in analyzing and detecting both positive and negative social interactions in term of feeding behavior among individual cows in the experiment on foreground video stream using Long-term Recurrent Convolution Networks (LRCNs) model.

The system implementation and testing were performed on seven dairy cows in the feeding area. The ultra-wideband technology embedded tracking system recorded an accuracy with mean error of 0.39m and standard deviation of 0.62m. The detection accuracy of social interactions experiment reached 93.2%. However, the detection accuracy of the Real-time Locating System (RTLS) is not sufficient in identifying individual cows if in close body contact. Table 1 shows the comparison of main research work on animal identification in terms of the advantages and disadvantages of the techniques used.

Table 1. Comparison of main research works on animal (cattle, goats and pigs) identification in terms of the advantages and disadvantages of the technique used.

Work	Technique	Advantages	Disadvantages
Ahmed *et al.* (2015)	SURF features with two powerful classifiers: Minimum distance	• Works well in resolving animal invasive identification methods.	• Sensitive to image quality.

	and SVM and LDA algorithm		• Does not work well in handling automated recognition.
Andrew *et al.* (2016)	Selective local coat pattern matching	• Scales well across small herds.	• Does not work well in handling social monitoring of herds in outdoor environments.
Jingqiu et al. (2017)	Image entropy	• Good for identification of moving cow object behavior against a complex background.	• Does not work well in integrating the time correlation of cow behaviors.
Andrew et al. (2017)	Computer vision pipelines utilizing deep neural architectures	• Works well in learning and distinguishing the properties of unique dorsal patterns and structures exhibited by the species individually.	• Does not work well in complicated setups such as faster-moving, larger herds and tight animal gatherings.
Kumar and Singh (2017)	A hybrid feature extraction and classification paradigm	• Provides better solutions to problems of traditional animal recognition-based methodologies, and livestock framework-based systems.	• Does not work for automated animal biometric-based recognition.
Cheema and Anand (2017)	Faster R-CNN	• Works well in detecting animals in images.	• Does not work well in detecting overlapped objects.
Zin et al. (2018)	Inter-frame differencing and horizontal histogram-based method	• Achieves accuracy of 86.8% for automatic cropping of cow's body region and 97.01% for cow's pattern identification.	• Limited to black and white body patterns of the Holstein cows which may not work well for color patterns.
Rivas et al. (2018)	Artificial intelligence-based CNNs	• Does not only work well for cow detection but any other object detection by following the same process of CNNs training.	• Does not work well in animal tracking and in identifying animal color, shape and size.
Norouzzadeh et al. (2018)	Deep convolutional neural networks	• Works well for identifying, counting and describing the behaviors	• Accuracy could be hurt if humans are more likely to accept

		of 48 species in the 3.2 million SS dataset.	incorrect suggestions from DNNs. • Cannot handle automatic multispecies images.
Zhao et al. (2019)	Template database	• Works well in updating the template dataset in the system without difficulty and delay to improve the vision system practicability for individual identification.	• Does not work well in extracting the binary information of the cow's body pattern.
Qiao et al. (2019)	Mask R-CNN	• Works well in contour extraction and instance segmentation.	• Does not work well in handling the segmentation of the overlapping regions of the cows and the explicit segmentation of cow's head, trunk and legs.
Liu et al. (2020)	Structural model	• Works well in representing both the positions of the cow's specific body parts and its overall spatial location.	• Does not work well in detecting pose variation of the cow's shape when computing the general relationships that constrain the key points in the cow's structural model.
Hu et al. (2020)	YOLO, Frame differencing and segmentation span analysis, AlexNet models, and SVM classifier	• Works well for the fusion of deep parts features.	• Does not work well in predicting correctly some samples of the validation set without the involvement of deep-edge features and fine-grained classification method.
Xu et al. (2020)	Mask R-CNN	• Has counting accuracy and average precision especially on the datasets with occlusion and overlapping.	• Does not work well in classifying cow objects.
Shao et al. (2020)	Convolutional neural networks (CNNs)	• Works well in clustering results of a motionless or continuously appearing target in entire images.	• Does not work well in combining results of different flight sections split from one flight.

			• Does not work well in merging detection results when an individual target appears irregularly in images.
Alameer et al. (2020)	YOLO9000 and Faster R-CNN with ResNet50 as a base model.	• Works well in detecting high-level sitting, lying and drinking postures of pigs. • YOLO9000 demonstrates high speed, precision of behavior detection and miss rate.	• Produces some localization errors.
Ghosh et al. (2021)	Deep CNN-based models	• Works well for identifying individual animal breeds.	• Does not work for tracking individual animals.
Qiao et al. (2021a)	Cohesive review	• The review summarizes and analyses the important existing methods employed in precision cow farming.	• Not comprehensive enough for cattle tracking and classification problems.
Su et al. (2022)	Siamese network guided by Attention Mechanism (AMTracker)	• Attention Mechanism works well in dealing with the similar target interference. • BiFPN module works well in fusing the features at all levels.	• Does not work for tracking a single individual goat in a group. • Does not work well in a complex scenario where a target is occluded by other goats.

4. 2. Body condition score evaluation

According to Alvarez et al. (2018), one of the most essential methods of aiding and promoting the well-being of animals is by improving their welfare through constant evaluation of their body condition score for healthy and productive state.

4. 2. 1. Body condition score of the farm animals

Body condition score system is a 5-point based scale for scoring the body condition of individual animals like cattle with point 1 indicating malnourished/emaciated cattle and point 5 indicating nourished/lardy cattle. These indicators basically represent two important values, namely (1) low values and (2) high values. Low values of body condition score are indicators of health related risks which if not addressed on time stand a threat to cattle productive rate (Bell et al., 2018).

It is a common custom practice among knowledgeable and experience farmers to manually obtain body condition score using physical methods (Salau et al., 2014). The main drawback in this practice is the effort exerted and time consumed in obtaining the score results which are most often skewed depending on the experience of individuals handling the system. To address the shortcoming in body condition score measurements for accurate readings, modern practice in animal husbandry involves employing the use of non-intrusive approach (Lynn et al., 2017) and high-tech sensors such as 2D/3D sensors (Zin et al., 2020) to obtain vital information about the animals for the evaluation of their body condition score. Although the supervised machine learning approach is designed to use large number of labeled datasets/images in training/supervising the machine learning algorithms, which helps in overcoming overfitting and classifying data or predicting outcomes accurately, the availability of large number of labeled datasets/images may become an issue when applying the model to small-scale animal husbandry.

4. 3. Live weight estimation

According to Bercovich et al. (2013), weight estimation is one of the most essential methods of optimizing animal's welfare and productiveness, growth performance and profitability, and diversification of animal's products.

4. 3. 1. Live weight estimation of the farm animals

Weight is one of the contributory factors that could determine animal activities such as normal/abnormal fertility, estrus, gestation, birth, lactation (Jaurena et al., 2005), and respiratory rate (Wu et al., 2020). Food ration, a fixed portion of food that is allotted (especially in times of scarcity) can be managed by mere measuring the live weight of the cattle. This kind of management tool and other state-of-the-art live weight estimating methods (Fordyce et al., 2013) are desirable for accurate smart animal husbandry applications. However, the disadvantages of most state-of-the-art live weight estimating methods outweigh their advantages with respect to cost of acquiring the tools needed for the setup, technical-know-how installation and application, time consumption, and stress and injury they cause to the animal (Dickinson et al., 2013).

Furthermore, the weight estimation method that involves morphological traits (volumes, ratios size, body height, body width, and body length) estimation of the animal can be used for live weight estimation of cattle and other varieties of animal studied in this paper based on 2D/3D sensors (Hansen et al., 2018). Although the technology of 3D mitigates notable problems associated with 2D technology, there is tendency for the extracted features to be influenced by the camera viewpoints thereby thwarting the accurate estimation of cattle live weight (Qiao et al., 2021a).

4. 4. Behavior recognition

In animal husbandry, behavioral changes in reproduction, postures, feeding and drinking rate could be recognized and monitored. On most occasions, compromised welfare and health of animals such as cattle, goats, sheep and pigs can be detected early by keen monitoring and observing changes in their behavioral traits for further analysis. Changes in these measures, if detected and recognized on time, can reduce their harmful effects such as lameness (Qiao et al., 2021b), and improve the management efficiency of large-scale animal husbandry.

4. 4. 1. Behavior recognition for animal measures

Jingqiu et al. (2017) in their study on cattle reproduction and healthy behavior recognition from mass surveillance video collected 400 cows (calves and lactating) for the study. The method was based on image entropy (analysis and activities). Minimum bounding box and contour mapping were calculated for the capture of rutting span behavior and hoof characteristics at real-time. Their results from hoof disease and heat in the reproduction experiment achieved greater than 80% recognition rates, and 3.28% and 5.32% false negative rates for estrus and hoof disease, respectively. Traditionally, animal behavior recognition methods involve detecting the animal heads or depending on extra tools. These methods are with shortcomings, and to overcome them, Jiang et al. (2020) proposed an efficient deep learning approach for recognizing behaviors of group-housed goats from video sequence. They recognized four types of behaviors that goats can exhibit such as active, inactive, eating and drinking behaviors, and this was by analyzing the relationship between the bounding boxes and the four types of behaviors based on spatial location and amount of temporal movement of bonding box centroids in the frames. With 17 frames per second, their experimental videos with YOLOv4 achieved average recognition accuracies of 97.87% for eating behavior, 98.27% for drinking behavior, 96.86% for active behavior, and 96.92% for inactive behavior.

Jiang et al. (2020) research work was similar to the one performed in Bello et al. (2022a) where cattle was used as the experiment data instead, and Mask R-CNN as one of the employed deep learning models achieved superiority over other models used with accuracies of 93.34% for eating behavior, 88.03% for drinking behavior, 93.51% for active behavior, and 93.38% for inactive behavior at 20 frames per second. Pig behavior recognition is another area of research in animal husbandry that dwells on detecting changes in pig behaviors as a useful measure for early signs detection of abnormal health, welfare and reproduction (Alameer et al., 2020).

In a large-scale animal husbandry with demanding conditions, visual imaging for detecting pig behaviors poses a challenge especially when apply for automatic detection. To address this challenge, Alameer et al. (2020) developed two detectors based on deep learning methods for group-housed pigs postures and drinking behaviors recognition. With 0.989 ± 0.009 under different settings, the ability of their automated methods was demonstrated for behavior identification of individual animals.

5. MAINSTREAM MACHINE LEARNING TECHNIQUES IN SMART ANIMAL HUSBANDRY

Mainstream technologies are very popular or familiar technologies to the target masses; they are conventionally accurate and reliable. For animal measures, many mainstream technologies have their unique techniques which make them superior to another. Convolution neural networks are the most common techniques that form the backbone of many mainstream technologies with ability to achieve accurate result-oriented image feature extraction and representation, which has continue to make them grow in the domain of vision and image processing (Bello et al., 2022b). Going by the wide acceptance and application of convolution neural networks-based methods in animal husbandry, the following sub-sections will discuss some machine learning’s convolution neural networks-based models applied frequently in the animal farm domain including support vector machines (SVMs).

5. 1. Machine learning (ML) models

The accuracy, effectiveness and efficiency of machine learning (ML) models in solving difficult tasks with little or no human intervention has earned their applications in animal husbandry wide acceptance for farm data analysis. The analysis of aforementioned animal husbandry data was made possible by these ML techniques. The machine learning-based models that have been widely employed in the analysis of animal husbandry data are artificial neural networks (ANN)-based CNN models such as deep learning models. We preferred to go deep more on deep learning models than other models being the most commonly employed models for superior performances in identifying and classifying animals, in addition to their effectiveness in overcoming the challenges of data complexity (i.e., big data). (Kamilaris et al., 2017) put so much emphasis on image data which is one of the data commonly used in identification and classification problems. Furthermore, size of data is an important factor to consider in any deep learning applications because; small-size can result to what is referred to as overfitting. However, deep learning models being effective tools for many related image analyses and recognition have been employed for smart animal husbandry. More detailed applications of selected deep learning techniques and support vector machines (SVMs) as machine learning tools to smart animal husbandry are presented below.

5. 1. 1. Support vector machines (SVMs)

SVMs-based analysis is a common ML method for classification and predictions. Some detection problems are categorized as classification problems while others are classified as regression problems. Linear models cannot be used to describe regression problems adequately as many problems in the real world are non-linear problems. In such cases, only non-linear models are suitable for the description using non-linear functions. Often, overfitting becomes a challenge due to SVMs regression technique that has a tendency to fit the training data perfectly, thereby worsening the prediction accuracy on testing data than it does on training data. More notable challenge with SVMs is the difficulty in interpreting the SVMs regression in comparison with more interpretable techniques by experts in the domain of animal husbandry. More animal researchers have employed SVMs in their classification and prediction tasks.

Andrew et al. (2016) proposed a fully automatic individual Holstein Friesian cow visual identification from dorsal RGB-D imagery. Support vector machines (SVMs) are used to generate predictions using radial basis function (RBF) kernels based on ASIFT descriptor structure. The system performs animal regions segmentation by fitting a depth model and then carries out ASIFT descriptors extraction over the detected area. SVMs are employed to learn a species-wide predictor of descriptor-individuality utilized to select and use features for the recovery of the cow's identity. Although the system has shown a high percentage of identification accuracy when tested on approximately 86,000 images of 40 individuals from the FriesianCows2015 dataset, it does not work well in handling social monitoring of herd in outdoor environments.

Cheema and Anand (2017) proposed a Faster R-CNN object detection framework to efficiently detect animals in images. They extracted features from AlexNet of the animal's flank and trained a linear SVMs classifier for the individual's recognition. They tested and evaluated their framework on varying camera trap tiger image datasets. Their recognition system was also evaluated using zebra and jaguar images to show its generalization to different patterned species.

Hu et al. (2020) used a trained support vector machines classifier for the classification of the cow images in their proposed non-contact cow identification method that is based on deep parts features fusion (DPFF). They applied You Only Look Once (YOLO) method in extracting the cow object in the side-view image, and for the extraction of the cow's head, trunk and leg parts, a part segmentation algorithm is employed using frame differencing and segmentation span analysis. Furthermore, the deep features of the cow's head, trunk and leg parts are extracted by three independent fine-tuned AlexNet models, and a weighted summation strategy is employed for the fusion of the features. Although the DPFF model achieves 98.36% accuracy in identifying cows, six samples were predicted incorrectly in the validation set due to lack of deep edge features and fine-grained classification method.

5. 1. 2. Deep learning techniques

Deep learning models with technical ability for top-notch feature extraction and image representation have continued to gain more popularity across different domains of animal husbandry for tasks such as cow image segmentation (Bello et al., 2021c; Bello et al., 2021d), extraction of cattle contour from image (Bello et al., 2021b), automatic dairy cow mastitis recognition (Xudong et al., 2020), and automatic cattle counting (Xu et al., 2020) and many more. Ghosh et al. (2021) performed an experiment on goat and pig breed datasets to find the optimal model that can identify individual breeds from their images using nine different deep CNN-based models. MobileNetV2 model has obtained 95% precision accuracy for goat breed classification, and InceptionV3 model has obtained 100% precision accuracy for pig breed classification. The performance of the two models is on a par with other models for classifying animal breeds. Miao et al. (2019) recently used various CNN architectures such as ResNet (He et al., 2016), AlexNet (Krizhevsky et al., 2012) and VGGNet (Simonyan & Zisserman, 2015) for the classification of 48 animal species using the Snapshot Serengeti (Swanson et al., 2015) dataset with 3.2 million camera-trap images.

They have achieved 96% classification accuracy. Jingqiu et al. (2017) proposed a method for object recognition based on image entropy; it is aimed at identifying the behavior of a cow object that is on the motion against a complicated background. They used the minimum bounding box and contour mapping for the automated capturing of behavioral and characteristic features displayed by the cow. Although the approach used has a time-saving advantage for cow breeders and yields a high recognition rate of estrus and hoof-disease of not less than 80%, the time correlation of cow behaviors is not integrated. Andrew et al. (2017) demonstrated the suitability of computer vision pipelines that utilize deep neural architectures to carry out automated Holstein Friesian cow detection in addition to individual identification in a farm setup based on Holstein Friesian dorsal coat patterns. They have shown that it is possible to perform robustly Friesian cow detection and localization with an accuracy of 99.3% on the available dataset. Although they have shown the capability of their method in the scenarios presented, they have not considered complicated setups such as faster-moving, larger herd and tight animal gatherings.

Kumar and Singh (2017) proposed a hybrid feature extraction approach based on captured muzzle point image pattern features using a low-cost camera for the automatic recognition and classification of the cow's breed. K-Nearest Neighbour (K-NN), Fuzzy-KNN (F-KNN), Decision Tree (DT), Gaussian Mixture Model (GMM), Probabilistic Neural Network (PNN), Multilayer Perceptron (MLP) and Naive Bayes Classification Models (NBCM) were employed. Although experimental results have revealed the performance of the proposed hybrid feature extraction and recognition approach over the state-of-the-art methods, the approach did not work for multi-modality-based animal recognition and automated animal biometric-based recognition.

Zin et al. (2018) explored and examined the utilization of image processing technologies in analyzing and identifying individual cows using the techniques of deep learning. The black and white body patterns of the cow are the main features considered for the identification. Inter-frame differencing and horizontal histogram-based approach are used to detect the body of the cow which has been placed on the Rotary Milking Parlour. The predefined distance value is employed for the cropping of the cow's body region which is used as input data for training the deep convolutional neural network.

Although the system achieves 86.8% accuracy for automatic cropping of cow's body region and 97.01% for cow's pattern identification, the accuracy of automatic detection and cropping of cows' body region still needs improvement. Rivas et al. (2018) employed artificial intelligence-based convolutional neural networks (CNNs) as a method to analyze the information contained in the images captured by a camera-installed drone in order to identify individual objects in the images. In their approach, they trained the CNNs not only for cow detection but for any other object detection by following the same process of CNNs training. Although they described the platform design for the analysis of information in real-time and its cow detection performance, there was no consideration for the use of animal tracking methods and identifiers such as color, shape and size.

Norouzzadeh et al. (2018) seek to (a) harness deep learning to automatically extract necessary features to detect, count and describe animals; and (b) apply their method on the world's largest dataset of wild animals i.e., the SS dataset (Swanson et al., 2015). Previous efforts to harness hand-designed features to classify animals include Swinnen et al. (2014), who attempted to distinguish the camera-trap recordings that do not contain animals or the target species of interest by detecting the low-level pixel changes between frames. Zhao et al. (2019) proposed a computer vision system for the individual identification of dairy cows. By using the videos that contain the side view of a cow in motion, the system is able to detect and locate the cow object and its body area as the individual identity information. They created a template database for matching and comparing unknown images to determine their identity. The results of their experiment show that the feature points in the body pattern of cows can be calculated accurately by using the SIFT method. 96.72% accuracy of one-step identification is achieved when FAST, SIFT and FLANN are used to detect, extract and match points. Irrespective of the drop to 95.41% of the identification accuracy that is achieved when ORB and BruteForce methods are combined, there is higher matching efficiency in their combination. When a two-step match method is employed, there is a 98.36% increase in the probability of the group containing the correct match. Although the template dataset in the system can be updated without difficulty and a delay is imposed to improve the vision system practicability for individual identification, the method for extracting the binary information of the cow body pattern has not been addressed.

Qiao et al. (2019) proposed a Mask R-CNN (He et al., 2017) deep-learning-based instance segmentation technique that could handle the problem of contour extraction and instance segmentation of cows in a real ranch environment. Their technique detects and extracts from the frames that contain the motion of the cows, and this is followed by enhancement of the image to reduce the influence of shadow and illumination, with the segmentation of the cows and extraction of the body contour completing the process. They employed a challenging dataset of cow images to train and test their approach.

Their experiment produced 0.92 Mean Pixel Accuracy (MPA) performance for cow segmentation and 33.56 pixels of Average Distance Error (ADE) for contour extraction making it better than other instance segmentation methods, namely Deep Mask (Pinheiro et al., 2015) and Sharp Mask (Pinheiro et al., 2016) instance segmentation methods. However, their technique does not consider multiple cow objects in the instance segmentation and contour extraction problem. Liu et al. (2020) proposed a practical system that detects in a video the recorded structural information about cows.

To form the cow structural model, they employed key features to represent both the positions of the cow's specific body parts and its overall spatial location, such as the joints from the head through the trunk to the legs. Two convolutional neural networks are applied to the detection system to extract the key features from the raw images and to select individual features for conversion into a structural model. A post-processing model was developed which would enable the system to work with different quality of videos captured on commercial farms during normal operation. Although the detection and tracking of multiple cow objects in the same frame at the same time with the provision of robust performance against challenges such as occlusion are all successfully addressed in the work, pose variation of the cow's shape was not addressed in computing the general relationships that constrain the keypoints in the cow structural model.

Xu et al. (2020) proposed an automated method for counting cattle in a quadcopter vision system using Mask R-CNN. They demonstrated the application of the Mask R-CNN framework for instance segmentation of the images of detected cow objects in the context of counting in different situations such as in pastures and feedlots. The optimal IOU threshold (0.5) and the full-appearance detection of the algorithm were verified through performance evaluation. Although the experimental results in their work show the system's potential to perform reliably with an accuracy of 94% in counting cows on pastures and 92% in feedlots, it does not work well for cow classification. Shao et al. (2020), in order to assist with the management of grazing cows, proposed a system based on Convolutional Neural Networks (CNNs) for cow detection and counting using aerial images captured by an Unmanned Aerial Vehicle (UAV).

The detection performance of their system is improved by taking the advantage of using the UAV images, which enables the prediction of the object's approximate size, when the assumption can be made of the height of UAV from the ground to be approximately constant. They resized the image that would serve as input to the CNN for both training and testing to an optimal resolution which is determined by the size of the object and the network's down-sampling rate.

To avoid counting repetition in images, they utilized a 3D model rebuilt by using the UAV images for clustering detection results. Although their experiment has shown a great improvement of the detection performance when optimal input resolution is used with an F-measure of 0.952, the detection performance decreases when their system is applied to fast-moving animals as well as different sizes of the cows, and it is not easy to combine results of different flight sections split from one flight.

Qiao et al. (2021a) presented a review work that summarizes and analyses the important existing methods employed in precision cow farming so that research can be facilitated and development of related areas promoted. The review is a perception for monitoring cows smartly for their identification, estimation of their weight and evaluation of their body condition score.

This is to address the stagnation in farming productivity caused by mixed traditional practice, instability in climate, and environmental and socio-economic phenomena. They posited that precision livestock farming has what it takes when it comes to individual animal analysis with sensors-acquired enormous amounts of data and perception tools smartly occupying its core.

From their review, they anticipated the development of smart perception for precision cow farming through automated technologies combined with deep learning technologies.

However, just like SVMs, deep learning techniques have their challenges. First, generalization of deep learning models to unfamiliar datasets or different species of animal is difficult. Second, large datasets in their thousands or even millions are required for the training of deep learning models depending on the problems to be solved and accuracy expected (Kamilaris and Prenafeta-Boldu, 2018). Fig. 4 depicts Fig. 1 to Fig. 3 as a visual summary of the smart animal husbandry applications.

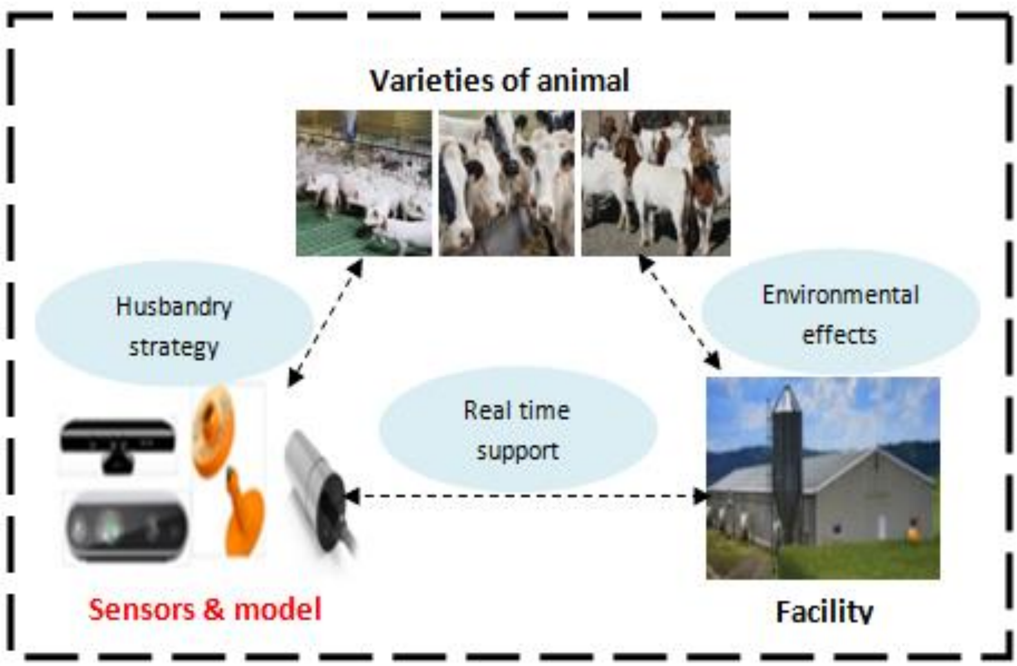

Fig. 4. Intelligent perception for smart animal husbandry applications

6. DISCUSSION

Having a good knowledge of the sources of smart animal husbandry data and their applications is a right step towards achieving a more productive animal farming. Animal measures as one of data sources in agriculture were critically examined in this paper for wider understanding as they have been utilized to assist in management decision making. Although we focus on applications and techniques of smart animal husbandry data, majority of our collected animal measures are on cattle with minimal contributions from other animals such as goat and pig. However, we have the notion that the findings in the paper can be extended to other animal species such as sheep. Several existing studies have reviewed applications of machine learning techniques in animal husbandry; however, only few of them addressed the specific data and machine learning techniques needed in smart animal husbandry applications, which makes the challenges involved in smart animal husbandry even more complex. Therefore, this section summarizes the challenges and the opportunities in smart animal husbandry.

6. 1. Challenges

The more the need for smart animal husbandry, the more the reasons to expect challenges as challenges are bound to exist where and when there are technological developments. Moreover, these challenges are even more pronounced with big data as its emergence has paved the way for the challenges that can be attributed to various data types (Alwis et al., 2022). The following challenges are the several main challenges in smart animal husbandry.

(1) Lack of generalization of models to new datasets or different species of animal: In deep learning applications, generalization of trained models to unfamiliar datasets or different species of animal is essential. However, there is what is called generalization gap in deep learning, a condition where it is difficult for a trained model to be tested with new datasets for classification or regression problems. This is a challenge in smart animal husbandry.

(2) Lack of large quantity of datasets: Large quantity of datasets is an important factor if successful training of models is anything to go by in deep learning tasks. In their thousands or even millions, large quantity of datasets are required for the training of deep learning models depending on the problems to be solved and accuracy expected (Kamilaris and Prenafeta-Boldu, 2018). Different data augmentation approaches such as random image cropping have been proposed in literature to increase the quantity of training images alongside their labels (Qiao et al., 2020). While some instances of publicly available datasets are high in quality, some are low in quality; example is MS COCO datasets that is significantly competitive with others such as ImageNet, PASCAL Visual Object Classes and SUN datasets in the number of instances per category. Moreover, a significant difference between the MS COCO cow dataset and other datasets is the number of labeled instances per image which may aid in contextual information learning. Another reason why MS COCO datasets look competitive is because MS COCO datasets are designed for detecting and segmenting objects occurring in their natural context. However, MS COCO cow dataset contains non-iconic (difficult) images with partial occlusion which do not usually help during training due to the noise and pollution that cause the learned model to be not good enough to withstand such unstable appearance. Also, the cow images in the MS COCO cow dataset are smaller and difficult to recognize without using more contextual reasoning.

(3) Problem of non-linearity of data: Linear models cannot be used to describe regression problems adequately as many problems in the real world are non-linear problems. In such cases, only non-linear models are suitable for the description using non-linear functions. Ability to solve problems involving non-linear problems with minimal resources using suitable algorithms is a challenge in the domain of smart animal husbandry.

(4) Difficulty in collecting real-time data for decision support: Collection of real time data and their timely utilization for decision support systems such as morphological

measures support systems, physiological measures support systems, and phenological measures systems could be a challenge in smart animal husbandry (Rojo-Gimeno et al., 2019). The physiological nature of animals permits their voluntary motion but without volition. Sometimes, due to urgency that may involve in the welfare and health of animals as living things, farmers need real time data and decision support system to make important decisions for the overall competitive and productive smart animal husbandry. Moreover veracity should be a watch word when accessing real time data and decision support system for decision making for maximum benefit (Moon et al., 2017). However, the veraciousness of data accessed via these channels is questionable and not trustworthy due to inadequate skills responsible for managing the way and manner such data are publicly reposited and transmitted (Neethirajan, 2020; Kamilaris et al., 2017), thereby negatively influencing data accuracy. Nevertheless, provision for simplified graphical user interface (GUI), and veracious repository can mitigate the negative influence of the aforementioned challenges, whereby achieving the goals of smart animal husbandry.

(5) Overfitting: Overfitting becomes a challenge when machine learning techniques such as SVMs regression technique that has a tendency to fit training data perfectly cannot do otherwise, thereby worsening the prediction accuracy on testing data than it does on training data. More notable challenge with SVMs is the difficulty in interpreting the SVMs regression in comparison with more interpretable techniques by experts in the domain of animal husbandry even as more animal researchers have employed SVMs in their classification and prediction tasks.

(6) Unpredictable environmental factors: Environmental factors such as climate, temperature, pollutants, food, population density, light, sound and parasites are important factors to consider when planning smart animal husbandry as they can pose several challenges in smart animal husbandry. For example, change in climatic conditions can result to unexpected rain or drought, this goes with other environmental factors aforementioned including socio-economic challenges which include data ownership claim.

(7) Skilled workforce: All in all smart animal husbandry needs competent hands to manage it. Skilled workforce with relevant experience suitable for specific work conditions is another challenge in the domain (Johnson, 2014). Worthy of future study are the following; (a) Strategy for overcoming all the raised challenges, (2) Contributory factors to farmers' lukewarm attitude towards smart animal husbandry (Regan, 2019).

6. 2. Opportunities

Smart animal husbandry technologies have their several opportunities. The challenges and risks involved in traditional method of practicing animal husbandry such as in nomadic system where farmers search for forage and water for animal life sustenance can be completely eradicated with the technologies of smart animal husbandry resulting in improved welfare and health of the animals and overall benefits for the farmers and researchers. The following opportunities are the several main opportunities of future research in smart animal husbandry.

(1) Hybridizing different species or varieties of animals: In smart animal husbandry applications, different species or varieties of animals can be hybridized and thus

produce their hybrids. It is an established fact that each individual animal has its own benefits, and hybridizing of various species and varieties of animal modalities can improve the overall performance. Hybridizing various species and varieties of animal modalities can have positive influence on the morphological, physiological and phenological aspects of the animal life cycle making them more productive and immune against diseases.

(2) Interdisciplinary opportunity: With smart animal husbandry, there is high tendency for interdisciplinary synergy with great impact on labor efficiency. The sum of individual effects as professionals cannot be equated to the effects of their synergy among which are farming cost reduction, efficient labor force (JiHye et al., 2017), knowledge sharing, access to big data and professional tools such as sensors to obtain parameters of the animal body size/shape features. Moreover, with smart animal husbandry, interdisciplinary of different branches of knowledge are incorporated for heuristic, iterative and reflexive management of the farm, which in turn enables individual farmer and researcher to discover information in an independent way for maintaining awareness to avoid any bias.

(3) Nonsubjective live weight estimation: Weight estimations are commonly employed to determine normal/abnormal fertility, estrus, gestation, birth, lactation (Jaurena et al., 2005), and respiratory rate (Wu et al., 2020). Often, the management tools and other state-of-the-art live weight estimation methods (Fordyce et al., 2013) are not robust enough and inaccurate to reflect the true live weight of the animals. Moreover, the cost of acquiring the tools needed for the weight estimation, the time consumption, the technical-know-how involved in the installation and application, stress and injury they cause to the animal (Dickinson et al., 2013) are worthy of future research. Although the morphological traits such as volumes, ratios size, body height, body width and body length estimation can be used for live weight estimation of the animal based on 2D/3D sensors (Hansen et al., 2018), there is tendency for the extracted features to be influenced by the camera viewpoints, thereby thwarting the accurate estimation of animal live weight (Qiao et al., 2021a). Therefore, it is important to device an objective measure for live weight estimation contrary to the subjective live weight estimation that may be modified by individual bias.

7. CONCLUSION

A survey was conducted on smart animal husbandry in this paper. Three important areas were thoroughly examined; these include (1) Animal measures as smart animal husbandry data, (2) Applications of animal measures in smart animal husbandry, and (3) Mainstream machine learning techniques that are employed in smart animal husbandry analysis. By so doing, we were able to reveal the main challenges involved in each surveyed area and the opportunities therein of future research.

We hold the opinion that these challenges and opportunities if critically addressed would not only benefit the farmers and the researchers but anyone who is so intent on going into smart animal husbandry technologies. Other types of data, their applications and the technologies best suitable for their applications in smart animal husbandry are left as further work.

References

[1] Ahmed, S., Gaber, T., Tharwat, A., Hassanien, A.E.,Snáel, V., 2015. Muzzle-based cattle identification using speed up robust feature approach. *In: IEEE International Conference on Intelligent Networking and Collaborative Systems*, pp. 99-104.

[2] Alameer, A., Kyriazakis, I., Bacardit, J., 2020. Automated recognition of postures and drinking behaviour for the detection of compromised health in pigs. *Scientific Reports* 10, 1-15.

[3] Allen, A., Golden, B., Taylor, M., Patterson, D., Henriksen, D., Skuce, R., 2008. Evaluation of retinal imaging technology for the biometric identification of bovine animals in Northern Ireland. *Livestock Science* 116, 42-52.

[4] Alvarez, J.R., Arroqui, M., Mangudo, P., Toloza, J., Jatip, D., Rodríguez, J.M., ..., Mateos, C., 2018. Body condition estimation on cows from depth images using convolutional neural networks. *Computers and Electronics in Agriculture* 155, 12-22.

[5] Andrew, W., Greatwood, C., Burghardt, T., 2017. Visual localisation and identification of Holstein Friesian cows via deep learning. In: *Proceedings of the IEEE International Conference on Computer Vision Workshops*, Venice, Italy, pp. 2850-2859.

[6] Andrew, W., Hannuna, S., Campbell, N., Burghardt, T., 2016. Automatic individual Holstein Friesian cows identification via selective local coat pattern matching in RGB-D imagery. In: *IEEE International Conference on Image Processing (ICIP)*, Phoenix, AZ, USA, pp. 484-488.

[7] Arslan, A.C., Akar, M., Alagöz, F., 2014. 3D cow identification in cattle farms. In: *IEEE 22nd Signal Processing and Communications Applications Conference (SIU)*, pp. 1347-1350.

[8] Bell, M.J., Maak, M., Sorley, M., Proud, R., 2018. Comparison of methods for monitoring the body condition of dairy cows. *Frontiers in Sustainable Food Systems* 80, 1-7.

[9] Bello, R.W., Abubakar, S., 2019. Development of a software package for cattle identification in Nigeria. *Journal of Applied Sciences and Environmental Management* 23, 1825-1828.

[10] Bello, R.W., Abubakar, S., 2020. Framework for modeling cattle behavior through grazing patterns. *Asian J. Mathemat. Sci.* 4, 75-79.

[11] Bello, R.W., Moradeyo, O.M., 2019. Monitoring cattle grazing behavior and intrusion using global positioning system and virtual fencing. *Asian Journal of Mathematical Sciences* 3, 4-14.

[12] Bello, R.W., Talib, A.Z., Mohamed, A.S.A., Olubummo, D.A., Otobo, F.N., 2020a. Image-based individual cow recognition using body patterns. *Intern. J. Adv. Comp. Sci. Appl.* 11, 92-98.

[13] Bello, R.W., Talib, A.Z.H., Mohamed, A.S.A.B., 2020b. Deep learning-based architectures for recognition of cow using cow nose image pattern. *Gazi University Journal of Science* 33, 831-844

[14] Bello, R.W., Talib, A.Z.H., Mohamed, A.S.A.B., 2021a. Deep belief network approach for recognition of cow using cow nose image pattern. *Walailak Journal of Science and Technology* 18, 1-14.

[15] Bello, R.W., Talib, A.Z.H., Mohamed, A.S.A.B., 2020d. A framework for real-time cattle monitoring using multimedia networks. *Intern. J. Recent Technol. Engin.* 8, 974-979.

[16] Bello, R.W., Mohamed, A.S.A., Talib, A.Z., 2021b. Contour extraction of individual cattle from an image using enhanced mask R-CNN instance segmentation method. *IEEE Access* 9, 56984-57000.

[17] Bello, R.W., Mohamed, A.S.A., Talib, A.Z., 2021c. Enhanced mask R-CNN for herd segmentation. *International Journal of Agricultural and Biological Engineering* 14, 238-244.

[18] Bello, R.W., Mohamed, A.S.A., Talib, A.Z., Olubummo, D.A., Enuma, O.C., 2021d. Enhanced deep learning framework for cow image segmentation. *IAENG International Journal of Computer Science* 48, 1182-1191.

[19] Bello, R.W., Mohamed, A.S.A., Talib, A.Z., Sani, S. & Wahab, M.N.A., 2022a. Behavior recognition of group-ranched cattle from video sequences using deep learning. Indian Journal of Animal Research, volume 56 issue: 505-512. doi: 10.18805/IJAR.B-1369

[20] Bello, RW., Mohamed, A.S.A., Talib, A.Z., 2022b. Cow image segmentation using mask R-CNN integrated with grabcut. In: *Proceedings of International Conference on Emerging Technologies and Intelligent Systems (ICETIS)* 2021, Springer, Cham, Lecture Notes in Networks and Systems 322, 23-32.

[21] Bello, R.W., Olubummo, D.A., Seiyaboh, Z., Enuma, O.C., Talib, A.Z., Mohamed, A.S.A., 2020c. Cattle identification: the history of nose prints approach in brief. In: *IOP Conference Series: Earth and Environmental Science*, 594, 1-9.

[22] Bercovich, A., Edan, Y., Alchanatis, V., Moallem, U., Parmet, Y., Honig, H., ..., Halachmi, I., 2013. Development of an automatic cow body condition scoring using body shape signature and Fourier descriptors. *Journal of Dairy Science* 96, 8047-8059.

[23] Blancou, J., 2001. A history of the traceability of animals and animal products. Revue Scientifique et Technique (International Office of Epizootics) 20, 413-425.

[24] Cai, C., Li, J., 2013. Cattle face recognition using local binary pattern descriptor. In: *IEEE Asia-Pacific Signal and Information Processing Association Annual Summit and Conference*, pp. 1-4.

[25] Caria, M., Schudrowitz, J., Jukan, A., Kemper, N., 2017. Smart farm computing systems for animal welfare monitoring. In: *IEEE 40th International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO)*, pp. 152-157.

[26] Cheema, G.S., Anand, S., 2017. Automatic detection and recognition of individuals in patterned species. In: *Joint European Conference on Machine Learning and Knowledge Discovery in Databases*, Springer, Cham, pp. 27-38.

[27] Chen, G., Shen, S., Wen, L., Luo, S., Bo, L., 2020. Efficient pig counting in crowds with keypoints tracking and spatial-aware temporal response filtering. In: *Proceedings of the IEEE International Conference on Robotics and Automation (ICRA),* Paris, France, pp. 1-7.

[28] Cowton, J., Kyriazakis, I., Bacardit, J., 2019. Automated individual pig localisation, tracking and behaviour metric extraction using deep learning. *IEEE Access* 7, 108049-108060.

[29] De Alwis, S., Hou, Z., Zhang, Y., Na, M.H., Ofoghi, B., Sajjanhar, A., 2022. A survey on smart farming data, applications and techniques. *Computers in Industry* 138, 1-14.

[30] Dickinson, R.A., Morton, J.M., Beggs, D.S., Anderson, G.A., Pyman, M.F., Mansell, P.D., Blackwood, C.B., 2013. An automated walk-over weighing system as a tool for measuring liveweight change in lactating dairy cows. *Journal of Dairy Science* 96, 4477-4486.

[31] Donahue, J., Anne Hendricks, L., Guadarrama, S., Rohrbach, M., Venugopalan, S., Saenko, K., Darrell, T., 2015. Long-term recurrent convolutional networks for visual recognition and description. In: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition,* Boston, MA, USA, pp. 2625-2634.

[32] Evans, J., Van Eenennaam, A., 2005. Livestock identification. An introduction to electronic animal identifications systems and comparison of technologies. Emerging management systems in animal identification 1-12 [Disponible en Línea: http://animalscience. ucdavis.edu/animalID/]

[33] FAO., 2009. How to feed the world in 2050. In: Food and Agriculture Organization of the United Nations, Rome.

[34] Feichtenhofer, C., Fan, H., Malik, J., He, K., 2019. Slowfast networks for video recognition. In: *Proceedings of the IEEE/CVF International Conference on Computer Vision*, Seoul, Korea (South), pp. 6202-6211.

[35] Fordyce, G., Anderson, A., McCosker, K., Williams, P.J., Holroyd, R.G., Corbet, N.J., Sullivan, M.S., 2013. Liveweight prediction from hip height, condition score, fetal age and breed in tropical female cattle. *Animal Production Science* 53, 275-282.

[36] Gebbers, R., Adamchuk, V.I., 2010. Precision agriculture and food security. *Science* 327, 828–831.

[37] Ghirardi, J.J., Caja, G., Garín, D., Casellas, J., Hernández-Jover, M., 2006. Evaluation of the retention of electronic identification boluses in the forestomachs of cattle. *Journal of Animal Science* 84, 2260-2268.

[38] Ghosh, P., Mustafi, S., Mukherjee, K., Dan, S., Roy, K., Mandal, S.N., Banik, S., 2021. Image-based identification of animal breeds sing deep learning. In: Deep Learning for Unmanned Systems, Springer, Cham, pp. 415-445.

[39] Hansen, M.F., Smith, M.L., Smith, L.N., Jabbar, K.A., Forbes, D., 2018. Automated monitoring of dairy cow body condition, mobility and weight using a single 3D video capture device. *Computers in Industry* 98, 14-22.

[40] He, K., Gkioxari, G., Dollár, P., Girshick, R., 2017. Mask R-CNN. In: *Proceedings of the IEEE International Conference on Computer Vision*, Venice, Italy, pp. 2961-2969.

[41] He, K., Zhang, X., Ren, S., Sun, J., 2016. Deep residual learning for image recognition. In: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, Las Vegas, NV, USA, pp. 770-778.

[42] Held, D., Thrun, S., Savarese, S., 2016. Learning to track at 100 fps with deep regression networks. In: *European Conference on Computer Vision*, Springer, Cham, pp. 749-765.

[43] Hu, H., Dai, B., Shen, W., Wei, X., Sun, J., Li, R., Zhang, Y., 2020. Cow identification based on fusion of deep parts features. *Biosystems Engineering* 192, 245-256.

[44] Jaurena, G., Moorby, J.M., Fisher, W.J., Cantet, R., 2005. Association of body weight, loin longissimus dorsi and backfat with body condition score in dry and lactating Holstein dairy cows. *Animal Science* 80, 219-223.

[45] Jiang, M., Rao, Y., Zhang, J., Shen, Y., 2020. Automatic behavior recognition of group-housed goats using deep learning. *Computers and Electronics in Agriculture* 177, 1-13.

[46] JiHye, O., Noh, D.H., Sohn, Y.H., 2017. Empirical test of Wi-Fi environment stability for smart farm platform. In: *4th International Conference on Computer Applications and Information Processing Technology (CAIPT),* pp. 1-5.

[47] Jingqiu, G., Zhihai, W., Ronghua, G., Huarui, W., 2017. Cow behaviour recognition based on image analysis and activities. *International Journal of Agricultural and Biological Engineering* 10, 165-174.

[48] Kamilaris, A., Gao, F., Prenafeta-Boldú, F.X., Ali, M.I., 2016. Agri-IoT: A semantic framework for Internet of Things-enabled smart farming applications. In: *IEEE 3rd World Forum on Internet of Things (WF-IoT),* Reston, VA, USA, pp. 442–447.

[49] Kamilaris, A., Kartakoullis, A., Prenafeta-Boldú, F.X., 2017. A review on the practice of big data analysis in agriculture. *Computers and Electronics in Agriculture* 143, 23-37.

[50] Kamilaris, A., Prenafeta-Boldú, F.X., 2018. Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture* 147, 70-90.

[51] Krizhevsky, A., Sutskever, I., Hinton, G.E., 2012. Imagenet classification with deep convolutional neural networks. *Advances in Neural Information Processing Systems* 25, 1097-1105.

[52] Kumar, S., Pandey, A., Satwik, K.S.R., Kumar, S., Singh, S.K., Singh, A.K., Mohan, A., 2018. Deep learning framework for recognition of cattle using muzzle point image pattern. *Measurement* 116, 1-17.

[53] Kumar, S., Singh, S.K., 2017. Automatic identification of cattle using muzzle point pattern: a hybrid feature extraction and classification paradigm. *Multimedia Tools and Applications* 76, 26551-26580.

[54] Kumar, S., Singh, S.K., 2020. Cattle recognition: A new frontier in visual animal biometrics research. In: Proceedings of the national academy of sciences, *India Section A: Physical Sciences*, 90, 689-708.

[55] Kumar, S., Singh, S.K., Singh, A.K., 2017. Muzzle point pattern based techniques for individual cattle identification. *IET Image Processing* 11, 805-814.

[56] Kusakunniran, W., Wiratsudakul, A., Chuachan, U., Kanchanapreechakorn, S., Imaromkul, T., 2018. Automatic cattle identification based on fusion of texture features extracted from muzzle images. In: *IEEE International Conference on Industrial Technology (ICIT)*, pp. 1484-1489.

[57] Li, G., Huang, Y., Chen, Z., Chesser, G.D., Purswell, J.L., Linhoss, J., Zhao, Y., 2021. Practices and applications of convolutional neural network-based computer vision systems in animal farming: a review. *Sensors* 21, 1-44.

[58] Liaghat, S., Balasundram, S.K., 2010. A review: The role of remote sensing in precision agriculture. *Am. J. Agric. Biol. Sci.* 5, 50–55.

[59] Liu, H., Reibman, A.R., Boerman, J.P., 2020. A cow structural model for video analytics of cow health. arXiv preprint 1-13. arXiv:2003.05903

[60] Lu, Y., He, X., Wen, Y., Wang, P.S., 2014. A new cow identification system based on iris analysis and recognition. *International Journal of Biometrics* 6, 18-32.

[61] Lynn, N.C., Kyu, Z.M., Zin, T.T., Kobayashi, I., 2017. Estimating body condition score of cows from images with the newly developed approach. In: *18th IEEE/ACIS International Conference on Software Engineering, Artificial Intelligence, Networking and Parallel/Distributed Computing (SNPD)*, pp. 91-94.

[62] Mahmoud, H.A., Hadad, H.M.R.E., 2015. Automatic cattle muzzle print classification system using multiclass support vector machine. *International Journal of Image Mining* 1, 126-140.

[63] Marchant, J., 2002. Secure animal identification and source verification. JM Communications, UK, pp. 1-28.

[64] Miao, Z., Gaynor, K.M., Wang, J., Liu, Z., Muellerklein, O., Norouzzadeh, M.S., ..., Getz, W.M., 2019. Insights and approaches using deep learning to classify wildlife. *Scientific Reports* 9, 1-9.

[65] Moon, A., Kim, J., Zhang, J., Liu, H., Son, S.W., 2017. Understanding the impact of lossy compressions on IoT smart farm analytics. In: *IEEE International Conference on Big Data (Big Data)*, pp. 4602-4611.

[66] Neary, M., Yager, A., 2002. Methods of livestock identification. Purdue University Department of Animal Sciences, AS-556-W, pp 1-9.

[67] Neethirajan, S., 2020. The role of sensors, big data and machine learning in modern animal farming. *Sensing and Bio-Sensing Research* 29, 1-8.

[68] Norouzzadeh, M.S., Nguyen, A., Kosmala, M., Swanson, A., Palmer, M.S., Packer, C., Clune, J., 2018. Automatically identifying, counting, and describing wild animals in

camera-trap images with deep learning. In: *Proceedings of the National Academy of Sciences*, 115, E5716-E5725.

[69] Petersen, W.E., 1922. The identification of the bovine by means of nose-prints. *J. Dairy Sci.* 5, 249-58.

[70] Pinheiro, P.O., Collobert, R., Dollár, P., 2015. Learning to segment object candidates. arXiv preprint 1-10. arXiv:1506.06204v2

[71] Pinheiro, P.O., Lin, T.Y., Collobert, R., Dollár, P., 2016. Learning to refine object segments. In *European Conference on Computer Vision*, Springer, Cham, pp. 75-91.

[72] Qiao, Y., Kong, H., Clark, C., Lomax, S., Su, D., Eiffert, S., Sukkarieh, S., 2021a. Intelligent perception for cows monitoring: A review for cows identification, body condition score evaluation, and weight estimation. *Computers and Electronics in Agriculture* 185, 1-11.

[73] Qiao, Y., Kong, H., Clark, C., Lomax, S., Su, D., Eiffert, S., Sukkarieh, S., 2021b. Intelligent perception-based cattle lameness detection and behaviour recognition: A review. *Animals* 11, 1-20.

[74] Qiao, Y., Su, D., Kong, H., Sukkarieh, S., Lomax, S., Clark, C., 2020. BiLSTM-based individual cattle

[75] identification for automated precision livestock farming. In: *IEEE 16th International Conference on Automation Science and Engineering (CASE)*, pp. 967-972.

[76] Qiao, Y., Truman, M., Sukkarieh, S., 2019. Cows segmentation and contour extraction based on Mask R-CNN for precision livestock farming. *Computers and Electronics in Agriculture* 165, 1-9.

[77] Regan, Á., 2019. 'Smart farming' in Ireland: A risk perception study with key governance actors. *NJAS-Wageningen Journal of Life Sciences* 90, 1-10.

[78] Ren, K., Bernes, G., Hetta, M., Karlsson, J., 2021. Tracking and analysing social interactions in dairy cattle with real-time locating system and machine learning. *Journal of Systems Architecture* 116, 1-7.

[79] Rivas, A., Chamoso, P., González-Briones, A., Corchado, J.M., 2018. Detection of cows using drones and convolutional neural networks. *Sensors* 18, 1-15.

[80] Rojo-Gimeno, C., van der Voort, M., Niemi, J.K., Lauwers, L., Kristensen, A.R., Wauters, E., 2019. Assessment of the value of information of precision livestock farming: A conceptual framework. *NJAS-Wageningen Journal of Life Sciences* 90, 1-9.

[81] Salau, J., Haas, J.H., Junge, W., Bauer, U., Harms, J., Bieletzki, S., 2014. Feasibility of automated body trait determination using the SR4K time-of-flight camera in cow barns. *SpringerPlus* 3, 1-16.

[82] Salau, J., Lamp, O., Krieter, J., 2019. Dairy cows' contact networks derived from videos of eight cameras. *Biosystems Engineering* 188, 106-113.

[83] Saxena, L., Armstrong, L., 2014. A survey of image processing techniques for agriculture. In: *Proceedings of Asian Federation for Information Technology in*

Agriculture, Australian Society of Information and Communication Technologies in Agriculture, Perth, Australia, pp. 405-418.

[84] Shao, W., Kawakami, R., Yoshihashi, R., You, S., Kawase, H., Naemura, T., 2020. Cattle detection and counting in UAV images based on convolutional neural networks. *International Journal of Remote Sensing* 41, 31-52.

[85] Simonyan, K., Zisserman, A., 2014. Two-stream convolutional networks for action recognition in videos. arXiv preprint, 1-11. arXiv:1406.2199

[86] Simonyan, K., Zisserman, A., 2015. Very deep convolutional networks for large-scale image recognition. arXiv preprint 1-14. arXiv:1409.1556

[87] Su, Q., Tang, J., Zhai, M., He, D., 2022. An intelligent method for dairy goat tracking based on Siamese network. *Computers and Electronics in Agriculture* 193, 1-13.

[88] Swanson, A., Kosmala, M., Lintott, C., Simpson, R., Smith, A., Packer, C., 2015. Snapshot Serengeti, high-frequency annotated camera trap images of 40 mammalian species in an African savanna. *Scientific Data* 2, 1-14.

[89] Swinnen, K.R., Reijniers, J., Breno, M., Leirs, H., 2014. A novel method to reduce time investment when processing videos from camera trap studies. *PLoS One* 9, 1-7.

[90] Wu, D., Yin, X., Jiang, B., Jiang, M., Li, Z., Song, H., 2020. Detection of the respiratory rate of standing cows by combining the Deeplab V3+ semantic segmentation model with the phase-based video magnification algorithm. *Biosystems Engineering* 192, 72-89.

[91] Xu, B., Wang, W., Falzon, G., Kwan, P., Guo, L., Chen, G., …, Schneider, D., 2020. Automated cattle counting using Mask R-CNN in quadcopter vision system. *Computers and Electronics in Agriculture* 171, 1-12.

[92] Xudong, Z., Xi, K., Ningning, F., Gang, L., 2020. Automatic recognition of dairy cow mastitis from thermal images by a deep learning detector. *Computers and Electronics in Agriculture* 178, 1-11.

[93] Zhang, L., Gray, H., Ye, X., Collins, L., Allinson, N., 2019. Automatic individual pig detection and tracking in pig farms. *Sensors* 19, 1-20.

[94] Zhao, K., Jin, X., Ji, J., Wang, J., Ma, H., Zhu, X., 2019. Individual identification of Holstein dairy cows based on detecting and matching feature points in body images. *Biosystems Engineering* 181, 128-139.

[95] Zin, T.T., Phyo, C.N., Tin, P., Hama, H., Kobayashi, I., 2018. Image technology based cow identification system using deep learning. In: *Proceedings of the International MultiConference of Engineers and Computer Scientists*, pp. 236-247.

[96] Zin, T.T., Seint, P.T., Tin, P., Horii, Y., Kobayashi, I., 2020. Body condition score estimation based on regression analysis sing a 3D camera. *Sensors* 20, 1-9