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Abstract

Sheep management and production enhancement are difficult for farmers due to the lack of dynamic response and poor welfare of the sheep. Poor welfare needs to be mitigated, and each farm must receive an expert-level assessment of critical importance. To mitigate poor welfare, researchers have conducted machine learning-based studies to automate the sheep health behavior monitoring process instead of using manual assessment. However, failure to recognize some sheep health behaviors degrades the performance of the model. In addition, behavior challenges, parameters, and analysis must be considered when conducting a study based on machine learning. In this paper, we discuss the different challenges: what are the parameters of the sheep health behaviors, and how to analyze the sheep health behaviors for automated machine learning systems to be helpful in the long term? The hypothesis is based on a different review of the literature of precision-based animal welfare monitoring systems with the potential to improve management and production.

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Sheep health behavior analysis in machine learning: A short comprehensive survey

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ABSTRACT

Sheep management and production enhancement are difficult for farmers due to the lack of dynamic response and poor welfare of the sheep. Poor welfare needs to be mitigated, and each farm must receive an expert-level assessment of critical importance. To mitigate poor welfare, researchers have conducted machine learning-based studies to automate the sheep health behavior monitoring process instead of using manual assessment. However, failure to recognize some sheep health behaviors degrades the performance of the model. In addition, behavior challenges, parameters, and analysis must be considered when conducting a study based on machine learning. In this paper, we discuss the different challenges: what are the parameters of the sheep health behaviors, and how to analyze the sheep health behaviors for automated machine learning systems to be helpful in the long term? The hypothesis is based on a different review of the literature of precision-based animal welfare monitoring systems with the potential to improve management and production.

1. Introduction

The sheep industry is gaining substantial benefits from the integration of automated breed identification systems. For livestock producers, the ability to quickly and accurately determine the various sheep's within a flock is of crucial importance when assessing their economic value and potential. However, for many farmers, particularly those lacking extensive practice and experience, identifying sheep can prove to be a challenging endeavor [1]. While DNA testing represents a viable option for breed identification [2], the real-time assessment of large sheep populations within production scenarios remains an unfeasible prospect [3]. This underscores the critical need for autonomous systems capable of proficiently and precisely identifying sheep in a farm environment. Understanding and monitoring sheep behavior, including standing, laying, and eating, is crucial for animal welfare and agricultural productivity. Changes in these behaviors may indicate health or psychological issues [4].

Beyond the intricacies of breed identification, the lives of sheep are far from simple. These animals are susceptible to injuries and illnesses, prompting veterinarians to employ various methods in gauging their levels of suffering [5,6]. However, traditional manual evaluation methods are time-consuming and often prone to errors. Therefore, researchers have turned to deep learning and machine learning-based assessment approaches to assess the health status of sheep [5,7–9]. Machine learning is a field of artificial intelligence that focuses on developing algorithms and models that enable computers to learn from and make predictions or decisions based on data, without being explicitly programmed. It involves training a machine to recognize patterns and relationships in data. While deep learning is a subfield of machine learning that specifically deals with neural networks composed of many layers, called deep neural networks. These networks are designed to automatically learn and represent complex patterns and features from data, making them particularly well-suited for tasks like image and speech recognition, natural language processing, and more. Notably, Noor et al. [7] introduced a deep learning model predicated on facial expressions to identify pain in sheep, while Jwade et al. [5] devised an autonomous system capable of distinguishing sheep within their natural habitat, achieving an impressive 95.8% prediction accuracy for economic valuation. Salama et al. [10] proposed an approach that uses deep convolutional neural networks (CNNs) and Bayesian optimization for parameter tuning to automatically identify sheep from images. In this context, it becomes evident that the accurate assessment of sheep health behaviors mandates the consideration of a range of challenges, parameters, and analysis methods, as illustrated in Fig. 1. Additionally,

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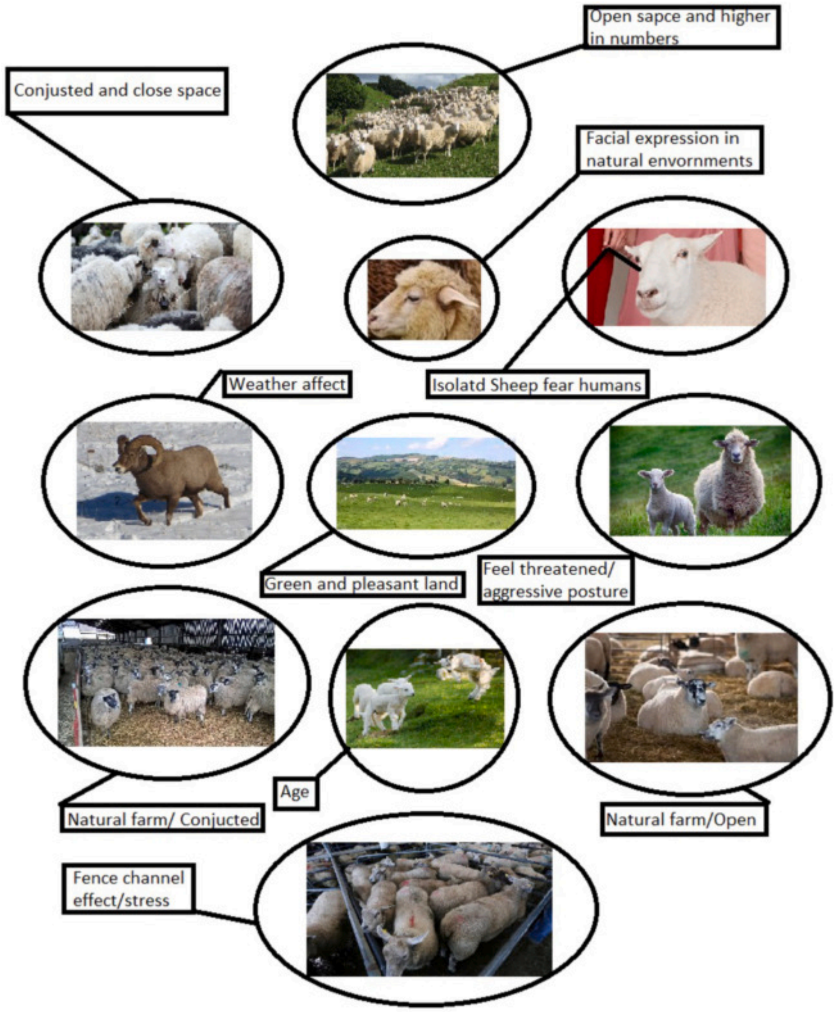

Fig. 1. Different sheep health behavior challenges and affect the Sheep's life.

various methodologies are outlined in Table 1, detailing the approaches used for the analysis, identification, classification, and detection of sheep health behaviors. However, these methods often lack certain parameters necessary for detecting and classifying the various behavioral patterns exhibited by different types of sheep.

This paper presents a comprehensive review of past research while introducing concrete behavioral challenges, parameters, and analytical perspectives pertinent to the evaluation of sheep health behaviors. Researchers embarking on machine learning or deep learning-based studies related to sheep health behaviors are urged to familiarize themselves with and adhere to these parameters. Nevertheless, they should remain cognizant that practical assessments might introduce distinct challenges.

This paper collectively demonstrates the versatility of machine learning techniques in addressing a multitude of sheep behavioral challenges. Moreover, we want to address and consider a comprehensive set of parameters and insights, challenges, and analytical methods when attempting to assess sheep behaviors accurately using machine learning. The rest of the paper is structured as follows: Section 2 delves into related works concerning sheep health behaviors assessments using machine learning and deep learning models, while Section 3 elucidates various parameters intrinsic to these behaviors. Section 4 outlines environmental and other challenges like genetic, followed by Section 5, which provides an in-depth analysis of sheep behavior. Finally, Section 6 engages in a comprehensive discussion and conclusion, culminating in this comprehensive review.

2. Related work

*T*he use of quantitative behavioral observations to assess sheep health and welfare has become a common practice. Within the sphere of farmers and livestock veterinarians, initial diagnoses often hinge on the discernment of broad behavioral alterations exhibited by the animals under their care [11]. Numerous studies have been conducted with the aim of identifying sheep behavior through classification, regression, and detection methodologies, as illustrated in Fig. 2. For example, Kleanthous et al. [12] are in the realm of advances in artificial intelligence using wearable sensors to discern health behaviors of sheep. Their research aims to consolidate previous studies concerning the efficacy of various types of sensors in recognizing agricultural sheep activities. The paper meticulously delves into data segmentation methodologies, offering insight into window size and sample rate selections. Similarly, Shahinfar et al. [6] focus on the early prediction of adult wool growth and quality in Australian merino sheep, employing machine learning techniques to assess the efficacy of animal husbandry practices. Meanwhile, Wang et al. [13] adopt an acoustic approach that takes advantage of the ability to accurately differentiate sheep activity. This enables the use of a wider range of factors derived from sheep health behavior to estimate intake, classification of behavior, and identification.

In the context of employing advanced technologies, recent advancements have demonstrated their potential in sheep management. For example, unmanned aerial vehicles (UAVs) have been used for sheep counting using a region-based computational neural network (R-CNN) system [14]. Ma et al. [15] delve into sheep identification and location,

Table 1
Machine learning and deep learning frameworks for sheep health behaviors and identification, classification, and detection types.

Ref	Input Data	Functionality	Models/Algorithms	Best Output
[19]	Accelerometer data	Classification of sheep health behaviors	Random Forest (RF), Short Term Memory (LSTM), Bidirectional LSTM (BLSTM)	LSTM 88.0%, RF 82.5% F1-score: BLSTM 0.84, LSTM 0.83, RF 0.65
[20]	Four types of Sheep breed images	Classification of sheep breeds	Ensemble model of the Residual Network (ResNet50) Visual Geometry Group (VGG16) Comparison: ResNet50, VGG16, VGG19, InceptionV3 and Xception	Accuracy: 97.32%
[21]	Sheep faces dataset	Face detection and classification	Faster R-CNN, ResNet50V2	Accuracy: 95.0%
[22]	Dataset of images of Sheep from a UAV at 80 m and 120 m	UAV for livestock monitoring and detection	U-Net-MS network	F1-score: 98%
[23]	B+LNZ dataset	Predicts sheep genetic relationship from faces	Kinship-based VGG19 CNN model	Face detection: 80% accuracy, kinship detection: 68% balanced accuracy
[24]	UAV Video Dataset	Sheep detection from UAVs	U-Convolutional Network (UNet)	Precision: 96.20%, Recall: 90.14%, F1-score: 93.07%, RMSE: 0.783
[25]	Sheep age dataset	Sheep age identification based on facial images	Faster R-CNN, and ResNet50V2	Two months: 95.4% Average accuracy, Sheep aged 5 months: 91.3% accuracy
[26]	Dataset has four classes (Himalayan bear, Marco Polo sheep, Snow leopard, and other animals)	Animal identification and classification	Inception v3 integrated with kNN classifier	98.3% accuracy
[27]	Kaggle sheep's dataset	Different sheep classification	Resnet-50, VGG-16	Resnet-50: 86% accuracy, VGG-16: 94% accuracy
[28]	Cattle and sheep images	recognition and identification	VGG-16 network	96.67% accuracy

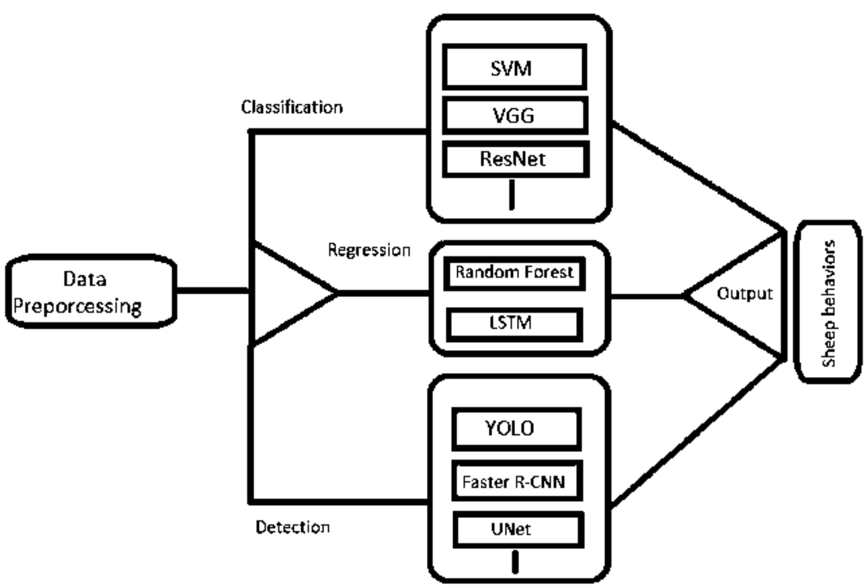

Fig. 2. Sheep health behaviors analysis using different machine learning and deep learning techniques.

introducing a neural network model based on the Faster-FCNN architecture with the Soft-NMS algorithm to monitor and identify sheep within complex rearing situations. Cheng et al. and Molapo et al. [16,17] incorporate YOLO v5 (You Only Look Once) into a deep learning model for recognizing sheep health behavior. Furthermore, Fogarty et al. [18] conduct an investigation into feature development and machine learning algorithms to optimize the precision of behavioral categorization in extensively grazed sheep by using an accelerometer on the ears.

3. Sheep behavior insights

Sheep are gregarious creatures; they graze, walk, run, and sleep in groups. The eldest ewe is generally the driving force behind such actions [29,30]. Regarding sheep daily routine of foraging for food, Grazing animals may spend most of sheep time foraging for food, depending on food availability, food quality and metabolic demands. Observing the amount of time a sheep spends ruminating gives an indication of animal welfare, but is also affected by food type and digestibility [31]. Grazing occurs in a regular 24-hour cycle, and most grazing occurs early in the morning and late in the afternoon. Several studies have emphasized the significance of behavior as an indication of pain in animals [32,33], and assessing behavior can provide further information on the condition of sheep. The sheep sleep for about four hours each day. Except for a few breeds, sheep come into oestrus when the days get shorter in the fall. During this time, the ewes will become more active and the rams may act aggressively. Lambs will reach puberty between 7 and 12 months of age. Sheep have a strong visual awareness, and they can recognize the faces of other sheep and discriminate between breed and sex, as well as species, based only on facial recognition [34]. Ewes utilize vocalization and hearing to communicate with their lambs and cope with stressful situations (the provision of feed or alarm). When they hear loud noises, they may get anxious. Sheep will undoubtedly avoid rotting feed.

4. Genetic & environmental challenges

Study of sheep welfare in farm production systems has led to a growing interest in the relative relevance of genetic and environmental components of sheep health behavior, their influence on the adaptation of the animal to the farm environment, and hence its welfare and productivity [35]. In addition, the housing needs of sheep differ from those of small animals. It is important to remember that the sheep developed from a mountain-dwelling, wild variety. It is doubtful that sheep would suffer from low temperatures due to their rumen, an internal fermentation chamber that generates heat. The goal should be to create housing that resembles the outdoors without snow, wind, and rain. Clean water must always be provided. Several studies have found that sheep prefer to drink from troughs rather than buckets [29].

Moreover, behavioral indicators are extensively used in current pain assessment methods because they are sensitive and non-invasive measurements of pain [36]. Studies of lambs that undergo tail curling and castration have shown pain-related behaviors, such as lip curling, shaking, aberrant postures, and vocalizations [37–39]. However, on-farm observation of behavioral changes can take considerable time, making it impracticable. Furthermore, due to the variable character of spontaneous pain, subtler alterations in sheep behavior are more likely to go unnoticed [40]. Disease is a primary cause of suffering in sheep, which has a detrimental influence on the animals' welfare and consequently impacts their production [41].

5. Behavioral analyzation

There are several significant and unexpected problems with health that influence the behavior of sheep. When it comes to assessing the health and well-being of sheep, one of the first telltale signs of a potential problem, whether it affects an individual sheep or an entire flock, manifests itself through deviations from their typical behavior [42]. These distinctive behavioral anomalies encompass a spectrum of actions, ranging from lethargy and a waning interest in food consumption to an increase in vocalization, instances of individuals isolating themselves from the flock, the emergence of pica tendencies, restlessness, and a noticeable elevation in respiratory rates [43,44], which can affect machine learning performance, and automated results could be unpredictable. Even though, within the specific conditions during the winter season, sheep had minimal influence on the waterway due to the high moisture content of the pasture, consequently leading to limited interaction [45].

Moreover, behavior stands out as an exceptionally sensitive indicator that effectively reflects common welfare challenges, including injuries, illnesses, and lower intake levels [46]. Its diagnostic potential makes it a valuable tool for assessing the overall welfare of sheep using machine learning predictive models. However, given its innate responsiveness to physiological and emotional states, behavioral shifts are essential to monitor as an integral part of comprehensive welfare evaluations, enabling swift identification and intervention.

Even though in the context of sheep management, the presence of experts plays a crucial role in the achievement of successful outcomes, as it guarantees the preservation of the animals' well-being as the primary goal. The animal behavior analysis experts have invested their time in sheep health behavior analysis for the responsibility of sheep care in a proactive and comprehensive approach towards managing the overall well-being of the sheep [47], which also helps the machine learning researchers conduct the experimental work [48]. The experts of animal science are Equipped with the capacity to identify atypical behaviors at an early stage and individuals who have received specialized training are more effective at quickly and efficiently addressing the root causes. By detecting anomalies in behavior, it is possible to proactively tackle welfare issues before they get worse, resulting in improved overall health outcomes for the sheep family.

6. Conclusion and discussion

Though sheep welfare study has failed for a decade, the consensus is that giving animals a “natural” being with fundamental behaviors and adequate space, like natural farming, maximizes welfare. Engaging the sheep farming community with the burgeoning domain of machine learning and deep learning-based animal behavior analysis introduces captivating challenges, parameters, and analytical avenues. This research advances methods for monitoring and analyzing sheep's health behavior features, improving animal welfare and production. The evolution of technology offers potential solutions to efficiently capture sheep welfare data, particularly in commercial live export contexts, despite the inherent challenges posed by environmental factors. However, machine learning and deep learning protocols encounter hurdles, necessitating adaptable data collection systems to navigate the intricate landscape of sheep health behavior intricacies.

This study uncovers remarkable aspects of sheep intelligence. Quick response to food calls, problem-solving, name recognition, and clicker-based training demonstrate their cognitive ability. Lambs learn to explore open spaces and follow their homes quickly. Incredibly, sheep's right temporal and frontal cortex can remember human and ovine faces for two years. This complex learning and behavior display present challenges and opportunities for the machine learning and deep learning community. Precision-based behavior parameters and meticulous analysis hold the potential to forge an effective machine learning system for the identification of sheep health behaviors.

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Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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Data availability

No data was used for the research described in the article.

References

[1] C.M. Dwyer, A.B. Lawrence, A review of the behavioural and physiological adaptations of hill and lowland breeds of sheep that favour lamb survival, Appl. Anim. Behav. Sci. 92 (3) (2005) 235–260, International Society for Applied Ethonolgy Special Issue, https://doi.org/10.1016/j.applanim.2005.05.010, https://www.sciencedirect.com/science/article/pii/S0168159105001437, 2003.

[2] L.-J. Lawson Handley, K. Byrne, F. Santucci, S. Townsend, M. Taylor, M.W. Bruford, G.M. Hewitt, Genetic structure of European sheep breeds, Heredity, Nature 99 (2007) 620–631, https://doi.org/10.1038/sj.hdy.6801039.

[3] F. Montossi, M.F. i Furnols, M. del Campo, R. San Julián, G. Brito, C. Sañudo, Sustainable sheep production and consumer preference trends: compatibilities, contradictions, and unresolved dilemmas, in: 59th International Congress of Meat Science and Technology, 18–23 August 2013 Izmir/Turkey, Meat Sci. 95 (4) (2013) 772–789, https://doi.org/10.1016/j.meatsci.2013.04.048, https://www.sciencedirect.com/science/article/pii/S0309174013001708.

[4] K. Ren, J. Karlsson, M. Liuska, M. Hartikainen, I. Hansen, G.H. Jørgensen, A sensor-fusion-system for tracking sheep location and behaviour, Int. J. Distrib. Sens. Netw. 16 (5) (2020) 1550147720921776, https://doi.org/10.1177/1550147720921776.

[5] S. Abu Jwade, A. Guzzomi, A. Mian, On farm automatic sheep breed classification using deep learning, Comput. Electron. Agric. 167 (2019) 105055, https://doi.org/10.1016/j.compag.2019.105055, https://www.sciencedirect.com/science/article/pii/S0168169918318465.

[6] S. Shahinfar, K. Kelman, L. Kahn, Prediction of sheep carcass traits from early-life records using machine learning, Comput. Electron. Agric. 156 (2019) 159–177, https://doi.org/10.1016/j.compag.2018.11.021, https://www.sciencedirect.com/science/article/pii/S0168169918309736.

[7] A. Noor, Y. Zhao, A. Koubaa, L. Wu, R. Khan, F.Y. Abdalla, Automated sheep facial expression classification using deep transfer learning, Comput. Electron. Agric. 175 (2020) 105528, https://doi.org/10.1016/j.compag.2020.105528, https://www.sciencedirect.com/science/article/pii/S0168169920306633.

[8] Y. Xu, J. Nie, H. Cen, B. Wen, S. Liu, J. Li, J. Ge, L. Yu, Y. Pu, K. Song, Z. Liu, Q. Cai, Spatio-temporal-based identification of aggressive behavior in group sheep, Animals 13 (16) (2023), https://doi.org/10.3390/ani13162636, https://www.mdpi.com/2076-2615/13/16/2636.

[9] T. Hu, R. Yan, C. Jiang, N.V. Chand, T. Bai, L. Guo, J. Qi, Grazing sheep behaviour recognition based on improved yolov5, Sensors 23 (10) (2023), https://doi.org/10.3390/s23104752, https://www.mdpi.com/1424-8220/23/10/4752.

[10] A. Salama, A.E. Hassanien, A. Fahmy, Sheep identification using a hybrid deep learning and bayesian optimization approach, IEEE Access 7 (2019) 31681–31687, https://doi.org/10.1109/ACCESS.2019.2902724.

[11] D. Gougoulis, I. Kyriazakis, G. Fthenakis, Diagnostic significance of behaviour changes of sheep: a selected review, in: Special Issue: Sheep Diagnostic Medicine, Small Ruminant Res. 92 (1) (2010) 52–56, https://doi.org/10.1016/j.smallrumres.2010.04.018, https://www.sciencedirect.com/science/article/pii/S0921448810001136.

[12] N. Kleanthous, A.J. Hussain, W. Khan, J. Sneddon, A. Al-Shamma'a, P. Liatsis, A survey of machine learning approaches in animal behaviour, Neurocomputing 491 (2022) 442–463, https://doi.org/10.1016/j.neucom.2021.10.126, https://www.sciencedirect.com/science/article/pii/S0925231222003150.

[13] K. Wang, P. Wu, H. Cui, C. Xuan, H. Su, Identification and classification for sheep foraging behavior based on acoustic signal and deep learning, Comput. Electron. Agric. 187 (2021) 106275, https://doi.org/10.1016/j.compag.2021.106275, https://www.sciencedirect.com/science/article/pii/S0168169921002921.

[14] F. Sarwar, A. Griffin, P. Periasamy, K. Portas, J. Law, Detecting and counting sheep with a convolutional neural network, in: 2018 15th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS), 2018, pp. 1–6.

[15] C. Ma, X. Sun, C. Yao, M. Tian, L. Li, Research on sheep recognition algorithm based on deep learning in animal husbandry, J. Phys. Conf. Ser. 1651 (1) (2020) 012129, https://doi.org/10.1088/1742-6596/1651/1/012129.

[16] M. Cheng, H. Yuan, Q. Wang, Z. Cai, Y. Liu, Y. Zhang, Application of deep learning in sheep behaviors recognition and influence analysis of training data characteristics on the recognition effect, Comput. Electron. Agric. 198 (2022) 107010, https://doi.org/10.1016/j.compag.2022.107010, https://www.sciencedirect.com/science/article/pii/S0168169922003271.

[17] M. Molapo, C. Tu, D. Du Plessis, S. Du, Management and monitoring of livestock in the farm using deep learning, in: 2023 International Conference on Artificial Intelligence, Big Data, Computing and Data Communication Systems (icABCD), 2023, pp. 1–6.

[18] E.S. Fogarty, D.L. Swain, G.M. Cronin, L.E. Moraes, M. Trotter, Behaviour classification of extensively grazed sheep using machine learning, Comput. Electron. Agric. 169 (2020) 105175, https://doi.org/10.1016/j.compag.2019.105175, https://www.sciencedirect.com/science/article/pii/S0168169919318319.

[19] K.E. Turner, A. Thompson, I. Harris, M. Ferguson, F. Sohel, Deep learning based classification of sheep behaviour from accelerometer data with imbalance, Inf. Process. Agric. (2022), https://doi.org/10.1016/j.inpa.2022.04.001, https://www.sciencedirect.com/science/article/pii/S2214317322000415.

[20] D. Agrawal, S. Minocha, S. Namasudra, S. Kumar, Ensemble algorithm using transfer learning for sheep breed classification, in: 2021 IEEE 15th International Symposium on Applied Computational Intelligence and Informatics (SACI), 2021, pp. 199–204.

[21] A. Hitelman, Y. Edan, A. Godo, R. Berenstein, J. Lepar, I. Halachmi, Biometric identification of sheep via a machine-vision system, Comput. Electron. Agric. 194 (2022) 106713, https://doi.org/10.1016/j.compag.2022.106713, https://www.sciencedirect.com/science/article/pii/S0168169922000308.

[22] F. Sarwar, A. Griffin, S.U. Rehman, T. Pasang, Detecting sheep in uav images, Comput. Electron. Agric. 187 (2021) 106219, https://doi.org/10.1016/j.compag.2021.106219, https://www.sciencedirect.com/science/article/pii/S0168169921002362.

[23] L. Szymanski, M. Lee, Deep sheep: kinship assignment in livestock from facial images, in: 2020 35th International Conference on Image and Vision Computing, New Zealand (IVCNZ), 2020, pp. 1–6.

[24] F. Sarwar, A. Griffin, S.U. Rehman, T. Pasang, Towards detection of sheep onboard a uav, https://doi.org/10.48550/ARXIV.2004.02758, https://arxiv.org/abs/2004.02758, 2020.

[25] A. Hitelman, Y. Edan, A. Godo, R. Berenstein, J. Lepar, I. Halachmi, Short communication: the effect of age on young sheep biometric identification, Animal 16 (2) (2022) 100452, https://doi.org/10.1016/j.animal.2021.100452, https://www.sciencedirect.com/science/article/pii/S1751731121002986.

[26] S. Jamil, Fawad, M.S. Abbas, F. Habib, M. Umair, M.J. Khan, Deep learning and computer vision-based a novel framework for Himalayan bear, Marco polo sheep and snow leopard detection, in: 2020 International Conference on Information Science and Communication Technology (ICISCT), 2020, pp. 1–6.

[27] M.Z. Bimantoro, A.W.R. Emanuel, Sheep face classification using convolutional neural network, in: 2021 3rd East Indonesia Conference on Computer and Information Technology (EIConCIT), 2021, pp. 111–115.

[28] F. Sun, H. Wang, J. Zhang, A recognition method of cattle and sheep based on convolutional neural network, in: 2021 2nd International Seminar on Artificial Intelligence, Networking and Information Technology (AINIT), 2021, pp. 420–424.

[29] T. Bryson, The Sheep Housing Handbook / by Tom Bryson, Farming Press Ipswich, Suffolk, 1984.

[30] Z. Budrikis, Collective motion strategies of sheep, Nat. Rev. Phys. 5 (2) (2023) 82, https://doi.org/10.1038/s42254-023-00556-5.

[31] M. Wang, J. Alves, M. Tucker, W. Yang, K. Ruckstuhl, Effects of intrinsic and extrinsic factors on ruminating, grazing, and bedding time in bighorn sheep (ovis canadensis), PLoS ONE 13 (10) (2018), Oct 29, https://doi.org/10.1371/journal.pone.0206664.

[32] C.E. Short, Fundamentals of pain perception in animals, Appl. Anim. Behav. Sci. 59 (1) (1998) 125–133, https://doi.org/10.1016/S0168-1591(98)00127-0, https://www.sciencedirect.com/science/article/pii/S0168159198001270.

[33] P. Bateson, Assessment of pain in animals, Anim. Behav. 42 (5) (1991) 827–839, https://doi.org/10.1016/S0003-3472(05)80127-7, https://www.sciencedirect.com/science/article/pii/S0003347205801277.

[34] K.M. Kendrick, K. Atkins, M.R. Hinton, K.D. Broad, C. Fabre-Nys, B. Keverne, Facial and vocal discrimination in sheep, Anim. Behav. 49 (6) (1995) 1665–1676, https://doi.org/10.1016/0003-3472(95)90088-8, https://www.sciencedirect.com/science/article/pii/0003347295900888.

[35] B.T. Wolf, S.D. McBride, R.M. Lewis, M.H. Davies, W. Haresign, Estimates of the genetic parameters and repeatability of behavioural traits of sheep in an arena test, Appl. Anim. Behav. Sci. 112 (1) (2008) 68–80, https://doi.org/10.1016/j.applanim.2007.07.011, https://www.sciencedirect.com/science/article/pii/S0168159107002663.

[36] J.S. Mogil, S.E. Crager, What should we be measuring in behavioral studies of chronic pain in animals?, Pain 112 (2004) 12–15.

[37] C. Grant, Behavioural responses of lambs to common painful husbandry procedures, Appl. Anim. Behav. Sci. 87 (3) (2004) 255–273, https://doi.org/10.1016/j.applanim.2004.01.011, https://www.sciencedirect.com/science/article/pii/S0168159104000425.

[38] M. Guesgen, N. Beausoleil, E. Minot, M. Stewart, K. Stafford, Social context and other factors influence the behavioural expression of pain by lambs, Appl. Anim. Behav. Sci. 159 (2014) 41–49, https://doi.org/10.1016/j.applanim.2014.07.008, https://www.sciencedirect.com/science/article/pii/S0168159114002056.

[39] V. Molony, J.E. Kent, I.J. McKendrick, Validation of a method for assessment of an acute pain in lambs, Appl. Anim. Behav. Sci. 76 (3) (2002) 215–238, https://doi.org/10.1016/S0168-1591(02)00014-X, https://www.sciencedirect.com/science/article/pii/S016815910200014X.

[40] J.M. Foss, A.V. Apkarian, D.R. Chialvo, Dynamics of pain: fractal dimension of temporal variability of spontaneous pain differentiates between pain states, J. Neurophysiol. 95 (2) (2006) 730–736, https://doi.org/10.1152/jn.00768.2005.

[41] K.M. McLennan, C.J. Rebelo, M.J. Corke, M.A. Holmes, M.C. Leach, F. Constantino-Casas, Development of a facial expression scale using footrot and mastitis as models of pain in sheep, Appl. Anim. Behav. Sci. 176 (2016) 19–26, https://doi.org/10.1016/j.applanim.2016.01.007, https://www.sciencedirect.com/science/article/pii/S0168159116000101.

[42] D.R. Arney, Sheep behaviour, needs, housing and care, Scand. J. Lab. Anim. Sci. 36 (1) (2014) 69–73, https://doi.org/10.23675/sjlas.v36i1.170, https://ojs.utlib.ee/index.php/SJLAS/article/view/21516.

[43] R. Berthel, A. Deichelboher, F. Dohme-Meier, W. Egli, N. Keil, Validation of automatic monitoring of feeding behaviours in sheep and goats, PLoS ONE 18 (5) (2023) 1–19, https://doi.org/10.1371/journal.pone.0285933.

[44] B. Fan, R.H. Bryant, A.W. Greer, Automatically identifying sickness behavior in grazing lambs with an acceleration sensor, Animals 13 (13) (2023), https://doi.org/10.3390/ani13132086, https://www.mdpi.com/2076-2615/13/13/2086.

[45] A. Bunyaga, R. Corner-Thomas, I. Draganova, P. Kenyon, L. Burkitt, The behaviour of sheep around a natural waterway and impact on water quality during winter in New Zealand, Animals 13 (9) (2023), https://doi.org/10.3390/ani13091461, https://www.mdpi.com/2076-2615/13/9/1461.

[46] P.V. Steagall, H. Bustamante, C.B. Johnson, P.V. Turner, Pain management in farm animals: focus on cattle, sheep and pigs, Animals 11 (6) (2021), https://doi.org/10.3390/ani11061483, https://www.mdpi.com/2076-2615/11/6/1483.

[47] S. Brando, M. Norman, Handling and training of wild animals: evidence and ethics-based approaches and best practices in the modern zoo, Animals 13 (14) (2023), https://doi.org/10.3390/ani13142247, https://www.mdpi.com/2076-2615/13/14/2247.

[48] Y. Edan, G. Adamides, R. Oberti, Agriculture Automation, Springer International Publishing, Cham, 2023, pp. 1055–1078, https://doi.org/10.1007/978-3-030-96729-1_49.