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The groundbreaking impact of digitalization and artificial intelligence in sheep farming

Muhammad Furqan Arshad [a], Giovanni Pietro Burrai [a], Antonio Varcasia [a,*], Maria Francesca Sini [a], Fahad Ahmed [b], Giovanni Lai [a], Marta Polinas [a], Elisabetta Antuofermo [a], Claudia Tamponi [a], Raffaella Cocco [a], Andrea Corda [a], Maria Luisa Pinna Parpaglia [a]

[a] Department of Veterinary Medicine, University of Sassari, Sassari, Italy
[b] Nutrition Innovation Centre for Food and Health (NICHE), School of Biomedical Sciences, Ulster University, Coleraine BT52 1SA, UK

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ABSTRACT

The integration of digitalization and Artificial Intelligence (AI) has marked the onset of a new era of efficient sheep farming in multiple aspects ranging from the general well-being of sheep to advanced web-based management applications. The resultant improvement in sheep health and consequently better farming yield has already started to benefit both farmers and veterinarians. The predictive analytical models embedded with machine learning (giving sense to machines) has helped better decision-making and has enabled farmers to derive most out of their farms. This is evident in the ability of farmers to remotely monitor livestock health by wearable devices that keep track of animal vital signs and behaviour. Additionally, veterinarians now employ advanced AI-based diagnostics for efficient parasite detection and control. Overall, digitalization and AI have completely transformed traditional farming practices in livestock animals. However, there is a pressing need to optimize digital sheep farming, allowing sheep farmers to appreciate and adopt these innovative systems. To fill this gap, this review aims to provide available digital and AI-based systems designed to aid precision farming of sheep, offering an up-to-date understanding on the subject. Various contemporary techniques, such as sky shepherding, virtual fencing, advanced parasite detection, automated counting and behaviour tracking, anomaly detection, precision nutrition, breeding support, and several mobile-based management applications are currently being utilized in sheep farms and appear to be promising. Although artificial intelligence and machine learning may represent key features in the sustainable development of sheep farming, they present numerous challenges in application.

1. Introduction

In recent years, there has been an increasing trend towards larger and more intensive animal farming operations driven by the anticipated increase in the world's population to 9 billion people by 2050 (Béné et al., 2015). The Food and Agriculture Organisation of the United Nations (FAO) estimates that a roughly 70% increase in world food production will be required to adequately meet the needs of the growing global human population (Alexandratos and Bruinsma, 2012; FAO, 2009). As a result, there has been an increase in the number of sheep farms with higher animal density and corresponding higher sheep-to-stockperson ratio.

The integration of Artificial intelligence (AI)-based systems has strengthened the efficiency of precision livestock farming (Nolack Fote et al., 2020). The concept of using intelligence in computers was first described by Alan Turing in 1950 (Turing, 1950). The term "Artificial intelligence" was first coined by John McCarthy (father of AI) in 1956 during an academic conference (Andresen, 2002). It is the replication of human intelligence in machines making them able to perform complex actions and even predict an output (Tripathi, 2021). Additionally, the computer performs cognitive processes like humans do which includes reasoning, perceiving, learning, and interaction (Ergen, 2019). AI has completely transformed all industries. AI systems are now capable of performing self-learning (also known as machine learning) (Kaul et al., 2020). It has recently provided solutions to the analytical challenges encountered in animal farming and veterinary sciences (Cihan et al.,

* Corresponding author.
E-mail address: varcasia@uniss.it (A. Varcasia).

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2021).

There are approximately more than one billion sheep worldwide. The main sheep farming regions are found between latitudes of 30 and 45 degrees south in Australia, South America, and New Zealand, and between latitudes of 35 and 55 degrees north in Europe and Asia (Morris, 2017). Despite their huge numbers and presence in developed countries, sheep farms have been managed relatively with traditional approaches as compared to cattle (Morrone et al., 2022). Alapala Demirhan (2019) assessed the primary challenges associated with such farming practices, including labor intensiveness, the suboptimal quality of grazing land, insufficient breeding and genetic developments, elevated feed costs, vulnerability to predation, animal health issues, and adverse environmental impacts. Manual labour for watering, feeding and disease prevention is time-consuming and costly in terms of labour wages (Aubron et al., 2009). Furthermore, these conventional farming methods are highly prone to predator attacks, leading to economic losses due to a significant reduction in flock size (Morris, 2017). Additionally, record-keeping systems are absent in most traditional animal farms, making it impossible to monitor animal health, breeding history, effective herd management, and performance (Aldridge et al., 2019).

With the development of better precision livestock farming (PLF) practices, farmers are encouraged to adopt digital solutions for their sheep farms. PLF aims to manage individual animals by continuously monitoring production, health, reproduction, welfare, and environmental impacts in real-time with a set of electronic tools (Berckmans, 2017). In the intensive sheep farming systems, the adoption of different AI models such as machine learning (ML), deep learning (DL), and artificial neural networks (ANN) have converted conventional sheep farming into more sustainable, efficient, and profitable (Bao and Xie, 2022). Digital farming practice utilizing AI tools has paved the way for improved animal welfare and enhanced agricultural productivity (Antonik et al., 2022). It has enabled automation in monitoring sheep behaviour, health, nutrition, management, yield, and resource allocation (Bao and Xie, 2022; Ganai, 2022). With numerous sensors that track various animal variables like temperature, heart rate, and digestion, AI models enable farmers to manage their livestock (Basciftci and Gunduz, 2019).

Sheep farmers aspire to maximize profits by optimizing costs and revenue. Since improved animal welfare is directly linked to higher yields, farmers are encouraged to embrace modern AI-based digitalization in their sheep farms. Embracing data-driven farming significantly enhances farmer's decision-making capabilities (Jiménez et al., 2019). The use of smart applications enables sheep farmers to access enhanced markets, thereby bolstering sales (Dilleen et al., 2023; Odintsov Vaintrub et al., 2021).

The intersection of digital agriculture and artificial intelligence (AI) has unlocked new horizons in the realm of animal welfare. AI has permeated various industries, and its development and adaptability owe much to a collaborative, multidisciplinary effort involving professionals such as animal scientists, computer scientists, agricultural engineers, and environmental scientists. The incorporation of the latest AI technologies into animal welfare practices is a noteworthy development,

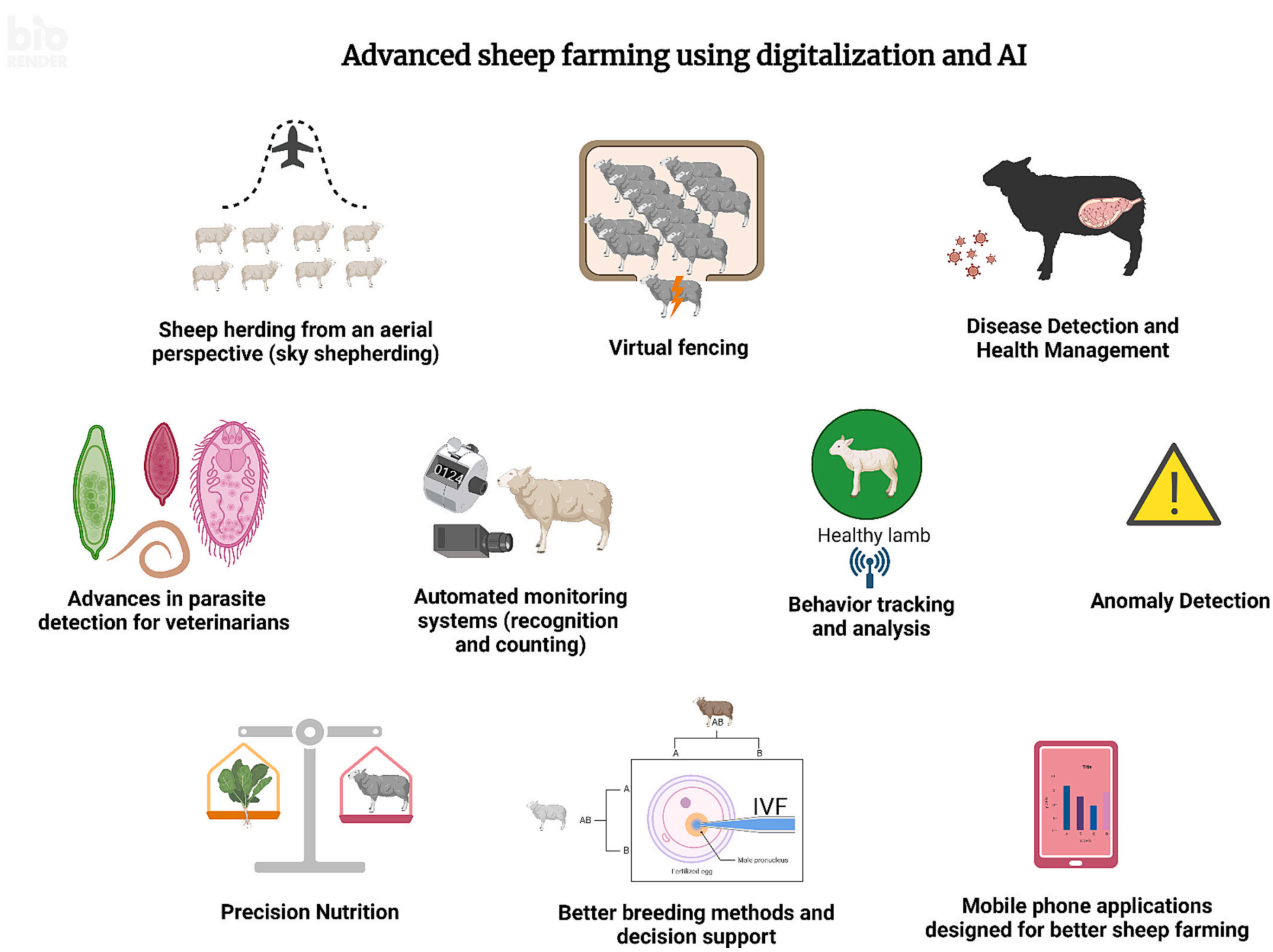

Fig. 1. Advanced sheep farming systems and approaches utilizing digital techniques and artificial intelligence (AI) for better sheep farming.

positioning AI as a sustainable solution to address the evolving needs of the industry. In this context, fast-paced research into AI for sheep welfare is not an exception. Global research has brought to light the potential integration of AI to enhance efficiency across multiple facets of sheep farming, encompassing sheep welfare, disease management, behavioural monitoring, optimization of feeding processes, and environmental supervision (Fig. 1).

A comprehensive coverage to the dynamic landscape of emerging technologies, with a focus on both digitalization and cutting-edge artificial intelligence techniques, and their collective impact on enhancing sheep welfare is therefore essential. In addition to this, the identification of formidable challenges is paramount, prompting the unveiling of new directions for future research. The overarching aim is to foster the efficient and sustainable integration of AI in modern sheep farming practices.

2. Digital and AI-based systems designed to aid precision farming of sheep

2.1. Sheep herding from an aerial perspective (sky shepherding)

The use of dogs in managing and safeguarding sheep from predators has been found to be highly effective since ancient times (Zingaro et al., 2018). However, it has been observed that this approach can induce chronic stress in sheep, characterized by elevated cortisol levels, primarily due to the vulnerable and social nature of sheep (EFSA panel on animal health and welfare, 2014; Terlouw et al., 2008). The repercussions of this stress can range from physical injuries to abortions in sheep (Phythian et al., 2011). Consequently, the aversive reactions triggered by the presence of these dogs underscore their significance but also raise concerns about their use in herding (Beausoleil et al., 2012).

A more promising alternative to using dogs is the integration of autonomous shepherding systems with AI. Drones have been explored for this purpose; a concept known as "sky shepherding". Research by Yaxley et al. (2021) has highlighted the potential of drones as a substitute for dogs in reducing stress among farm sheep. Drones can be programmed to emit various auditory cues to elicit specific responses from sheep flocks. Additionally, during nighttime operations, drones equipped with thermal infrared cameras can be employed to detect potential threats and raise alarms in case of intruders (Bondi et al., 2019). Another biomimetic surveillance system utilizes shepherding algorithms and can adapt to varying environmental conditions while guiding and protecting sheep, preventing them from entering sensitive or restricted areas (Strömbom and King, 2018).

2.2. Virtual fencing (VF)

A virtual fence utilizes a computerized system having the ability to create custom geometric boundaries without the use of any physical barrier or fence. On the other hand, conventional physical fencing (with a visible boundary) within sheep farms is known for its maintenance problems and the associated high expenses. A minimum of 3.5 miles of a barbed-wire fence is needed to enclose a 500-acre farm (Lipschitz, 2019). The adoption of virtual fencing technology (no-fence technology) presents numerous advantages including wildlife conservation, reduced overgrazing, and cost-effectiveness. This artificial intelligence-driven technology relies on a Global Positioning System (GPS) based virtual fencing system, rendering physical barriers unnecessary. When sheep attempt to breach the virtual boundary, they are either subjected to a sound signal or receive a mild electric stimulus via a digital neck collar (Brunberg et al., 2017; Jachowski et al., 2014; Umstatter, 2011).

In response to ethical concerns surrounding the use of electric stimuli, Marini et al. (2018) have devised a system that exclusively employs auditory signals to dissuade sheep from traversing the virtual perimeter. This approach utilizing sound signals alone has demonstrated its effectiveness as well. The utilization of sound signals for confining sheep within a virtual enclosure is also supported by other studies (Kleanthous et al., 2022; Campbell et al., 2021). A recent study conducted on sheep in Australia utilized same sound signals from a neck collar device. Here modified cattle eShepherd® device was used. The sheep were able to learn from the audio signals to stay within a specific zone without any physical barrier. There were some violations of the virtual boundary since the device was not originally meant to be used on sheep. Therefore, a more specific algorithm might prove better results for sheep. Moreover, a sheep breed with thick neck wool may respond less to the same audio cues than a sheep breed with reduced wool. Sheep can also develop insensitivity to the audio cues over time and a more intense audio signal might be required (Campbell et al., 2023).

2.3. Disease detection and health management

In the realm of sheep farming, there has been a notable development in the use of diagnostic tools that incorporate AI technologies and machine learning algorithms to identify potential health issues. For instance, a study concentrated on the application of AI to evaluate histology data, resulting in a notable improvement in the established murine intervertebral disc (IVD) degeneration model. This system also holds promise for detecting degenerative IVD changes in sheep (Alini et al., 2023). Furthermore, early detection of respiratory diseases in sheep has become feasible through the application of deep learning approaches (Cowton et al., 2018). Additionally, Digital Twin (DT) technology built on AI has shown significant potential in improving disease analysis and prediction achieving an impressive 92% response rate in analyzing the heartbeats of farm animals (Mishra and Sharma, 2023). Sheep body weight estimation could predict a lot about sheep health. González-García et al. (2018) designed a walk-over-weighing system for monitoring lightweight sheep. Another development involves the live estimation of sheep weight using LiteHRNet, a Lightweight High-Resolution Network that employs RGB-D images, offering an efficient, non-contact approach (He et al., 2023).

Computer vision techniques which employ infrared thermal imaging and visible imaging analysis are also being employed to enhance the monitoring of respiratory diseases (Jorquera-Chavez et al., 2019). A study conducted by Zhang et al. (2019) employed infrared technology to measure the body temperature of animals on a large farm and this technology can be further integrated with AI tools for automated monitoring of individual farm animals' body temperature. Several AI-based models have been proposed for the treatment of sheep diseases. One such embedded system that utilizes drones aimed at treating hydatidosis has been successfully tested (Caputo et al., 2022).

The application of machine learning in disease identification has often focused on image recognition. For example, for the accurate classification of skin and mammary tumors, machine learning-based algorithms have the ability to automatically analyse tissue slide images. These algorithms demonstrate the capability to differentiate between tumor and non-tumor classes (Burrai et al., 2023; Fragoso-Garcia et al., 2023). Machine learning has already been applied to epidemiological classification problems in animal science, for example, to predict exposure to bovine viral diarrhoea virus at the herd level and the distribution of herd exposure to liver fluke. It has been recently applied in the investigation of the transmission model of the mastitis pathogen in cattle (*Streptococcus uberis*) and the diagnosis of subclinical and clinical mastitis at the individual animal level. Using data from 1000 farms, Random Forest algorithms were able to replicate complex herd-level diagnoses made by veterinary specialists with a high degree of accuracy. An accuracy of 98%, a positive predictive value (PPV) of 86% and a negative predictive value (NPV) of 99% were achieved for the diagnosis of contagious bovine mastitis compared to environmental mastitis. Using an accurate, automated mastitis diagnosis tool can help non-specialist veterinarians make a rapid herd-level diagnosis and timely implement appropriate control measures for a disease that is deleterious in terms of animal health, productivity, well-being, and use of antimicrobials (Cockburn, 2020).

2.4. Advances in parasite detection for veterinarians

The use of conventional light microscopy remains the gold standard for identifying intestinal parasites in faecal samples, primarily due to its affordability and widespread availability. However, this method has several limitations, including being time-consuming, labor-intensive, less sensitive, and subject to interpretation biases (Murray, 2015). To address these shortcomings, the integration of artificial intelligence (AI) into clinical microbiology and parasitology laboratories has emerged as a promising alternative, capable of providing precise, sensitive, and swift results. A group of researchers developed a convolutional neural network (CNN) model by combining digital slide scanning with AI, demonstrating its ability to distinguish between positive and negative trichrome slides. This model has shown superior sensitivity and accuracy compared to manual examination (Mathison et al., 2020). Another study harnessed a trained deep neural network model that automatically focuses on and scans microscopic slides to identify *Schistosoma haematobium* eggs (Oyibo et al., 2022).

In addition, various studies have explored better approaches for parasite detection. A group of studies utilized a filter membrane with a 5 μm pore size to capture fluorescently labelled *Giardia* cysts, followed by image capture through a microscope-mounted camera (Koydemir et al., 2015) or a portable imaging flow cytometer (Göröcs et al., 2020). Machine learning algorithms trained to detect *Giardia* cysts are utilized to process these images, successfully achieving accurate detection, and counting. Moreover, emerging methods involve harnessing the power of machine learning to matrix-assisted laser desorption/ionization-time of flight (MALDI-TOF) mass spectra and whole-genome sequencing data. This approach holds promise for predicting drug resistance, detecting outbreaks, and enhancing diagnostics (Smith et al., 2020). In the market, there is an AI powered automated scanner known as "VETSCAN IMAGYST™," which utilizes deep learning algorithms to identify eggs in faecal slides (Nagamori et al., 2020).

Furthermore, some studies have showcased the use of highly specialized software capable of analyzing images on smartphone providing faecal egg counts, thereby reducing the dependence on manual counting. This approach is practical as modern smartphones come equipped with built-in sensors and offer a cost-effective solution to laborious microscopy (Kwon et al., 2016). On-site and rapid counting systems involving smartphone applications and machine learning have gained recognition as reliable counting mechanisms (Bucki et al., 2023). In the context of small ruminants, the Famacha© scoring system is commonly employed for detecting *Haemonchus contortus* infections by assessing the color of ocular conjunctival mucosa (Van Wyk and Bath, 2002). Anaemic sheep with white-colored conjunctival mucosa are considered positive for the infection, facilitating targeted deworming interventions. In this regard, a study has proposed a smartphone-based machine-learning application that uses the smartphone's camera to image the ocular conjunctival mucosa, classifying the animal as healthy or anaemic (de Souza et al., 2023).

2.5. Automated monitoring systems (Recognition and counting)

The utilization of automation in sheep farming has led to increased yield of animal products. To bolster decision-making in animal management, it is essential to focus on real-time data collection from the farm (Lewis Baida et al., 2021). The identification of individual sheep on the farm and their various behaviours is crucial for monitoring their health and other farming practices (Jin et al., 2022b, 2022a). Dore et al. (2021) have developed an automated tracking system based on millimeter-wave radars which offers precise and real-time animal monitoring. This system outperforms conventional video tracking as it is not sensitive to light variations, requires less processing power, and provides superior accuracy. The data generated can be integrated into AI-based systems capable of alerting farmers to any undesirable changes. Wang et al. (2021) have created a wearable multi-sensor system to assess sheep farming comfort. McLennan and Mahmoud (2019) have devised an automated system with the ability to detect changes in sheep facial expressions indicative of pain.

Advancements in deep learning technologies and computer vision have empowered precise animal management and increased profitability. Accurate sheep identification and counting are essential for effective large-scale farming (Song et al., 2022). Presently, most farms worldwide rely on manual counting, which has drawbacks such as double counting, omissions, low efficiency, and frequent counting requirements. Hence, the digitalization of sheep counting is gaining more attraction in the modern world. Various studies have introduced diverse sheep counting methods, including those employed by Zhang et al. (2022) who used goat head detection and AI-based automation through deep learning. Sarwar et al. (2018) employed a convolutional neural network (CNN) for sheep counting, while Deng et al. (2022) utilized the "You Only Look Once version 5" (YOLOv5) algorithm for sheep counting and management. The YOLO family is very peculiar in this regard. It is an AI model that detects a target in images or videos. This integrated system uses a camera to take photos or videos and feed the media into YOLO system. The system can accurately identify the targets, such as sheep, present within the input media, offering efficient detection and counting capabilities.

2.6. Behaviour tracking and analysis

Although it has long been believed that biological processes involving living things are too complicated to be controlled and monitored automatically, AI is opening possibilities for the development of completely automated online monitoring and management tools for animals. Effective management and welfare of sheep on farms as well as during their transportation between farms, can be monitored by observing sheep group dynamics, their positions, behaviours, and physiological indicators. Regular monitoring of sheep behaviour is valuable for early detection of diseases or any discomfort the sheep may experience in their environment, enabling farmers to enhance their well-being (Xu et al., 2021). The commonly used method for tracking animal behaviour is manual observation but this approach is inefficient, time-consuming, and impractical for larger farms (Keceli et al., 2020).

The application of AI and machine learning in monitoring farm sheep involves the interaction of computer algorithms, various biosensors, and data collection techniques. Biosensors are utilized to collect real-time data on various aspects such as animal behaviour, food intake, health, and environmental conditions. The data is then treated and evaluated using a system of data analysis, resulting in ordered datasets of prime importance that assist farmers in making timely decisions regarding sheep welfare (Mate et al., 2022). Several machine-learning algorithms have been adopted by researchers for monitoring animal behaviour in farm settings, including studies by Cheng et al. (2022) and Hu et al. (2023). They utilized YOLO5 model for behavioural analysis. The model first processed the input images of grazing sheep to train itself to recognize normal sheep behaviour. The model would then send an alarm if a varied behaviour is noted. In another study, researchers utilized GPS sensors and 3-D accelerometers attached to the neck. Videos of animal during rumination, grazing, lying down, and standing steadily were taken. An AI model was first trained to detect behavioural pattern with inputs in the form of videos and accelerometer data. The learned model can then accurately predict the animal behaviour remotely using GPS (Cabezas et al., 2022; Barwick et al., 2018).

2.7. Anomaly detection

In sheep farming, potential anomalies can include signs of illness, unusual patterns in flock behaviour, and unexpected environmental conditions, among other factors. Accurate prediction models have been built that send alerts to farmers based on data inputs from animals and the environment and can assist in detecting any deviation from what is normal. Farmers can readily implement corrective management strategies because of the comprehensive information provided by AI regarding the condition of their animals. Continuous technological advancements make it possible to create diagnostic tools capable of identifying anomalies without causing stress to the animal. This enables them to detect a disease outbreak days before farmers would even become aware of it (King, 2017; Griffith et al., 2013). In the foreseeable future, it is plausible that unmanned aerial vehicles (UAVs) will take flight every morning over animal farms to identify potential anomalies. Referred to simply as "drones", UAVs offer large-coverage and can acquire data in real-time. Jin et al. (2022b, 2022a) developed an AI model utilizing videos captured by drones. The model was trained to detect potential anomalies. Although, not tested on sheep farm, systems like this have the potential to be used in extensive sheep farming. One disadvantage of such system is the countless possibilities of different anomalies, making it challenging to train the system to detect every potential irregularity.

Evaluating the welfare of livestock is essential to prevent any deterioration in their well-being, enhance productivity, and identify signs of stress and injuries. In recent times, this assessment has also become a part of marketing strategies, as consumers increasingly demand humane treatment of animals on farms (Fuentes et al., 2022). Computer vision algorithms have been developed to identify irregularities in the farm environment, such as the presence of vehicles, intruders, or unauthorized access. One such detection system, developed by Yange et al. (2021) is based on a convolutional neural network (CNN). The CNN is a deep learning system that can process images and recognize patterns within it. In this study, they used CNN to recognize violence among animals. Thousands of images from violence and non-violence scenarios were fed to the CNN to train it to detect violence. Their model was able to detect violence in sheep farms with 93% accuracy. This is important in reducing losses in terms of animal injuries. Finally, an effective anomaly detection system should be capable of detecting problems in advance and have accurate predictive abilities which often necessitate the integration of AI-based technologies (Kozitsin et al., 2021).

2.8. Precision nutrition

The term "precision feeding" refers to the practice of providing farm animals with feed in quantities and compositions that align with their specific nutritional needs and bodily requirements (González et al., 2018). Various sensors and technologies have been developed for monitoring the nutrition of ruminants. This includes analytical tools such as data fusion, machine learning, and optimization techniques which can be integrated with this data (Cockburn, 2020; González et al., 2018). In the investigation conducted by Bosco et al. (2021), the adoption of precision feeding was observed to yield a pronounced reduction in the environmental footprint associated with ewe milk production. This reduction emanated from a substantial enhancement in milk production efficiency, achieving an increase of up to 50%. Regular interaction with sheep during milking in extensive sheep-farming environments provides valuable data that can be leveraged for improved breeding, feeding, and flock management by harnessing technological advancements (Vaintrub et al., 2021).

Regarding estimation of sheep forage intake which is usually referenced from cattle feed intake has been studied more widely. But this approach seems not appropriate. Accurate analysis of sheep feed intake is important as a representative of sheep health. In this regard, a study by Wang et al. (2022) utilized acoustic signals produced from chewing feed by sheep. These signals can be captured by a neck collar device and processed by a machine learning tool to predict any variation in feeding behaviour as an indicative of an illness. The sound signals from biting, chewing, and ruminating can be differentiated. Such a system is also utilized to keep track of forage intake by individual sheep. This information is important when rotational grazing is applied to have an estimation of forage requirements of a set number of sheep per hectare (Sheng et al., 2020). An interesting study utilized an AI model to predict metabolizable energy intake (MEI) using a wearable sensor. The sensor detected grazing time, speed, temperature, and other indicators. The estimation of accurate MEI is important for precision livestock feeding (Suparwito et al., 2021).

2.9. Better breeding methods and decision support

Digitalization and the utilization of AI have the potential to significantly enhance sheep farming by enabling the monitoring of reproductive data, genetic selection, and providing decision support. This includes optimizing breeding schedules, tracking heat data, identifying optimal mating pairs, selecting desirable genetic traits, and predicting breeding values. In modern animal breeding having access to accurate pedigreed data and sophisticated computational tools is fundamental. An online AI-based application called "Smart Sheep Breeder" (SSB) has been developed to automatically record performance data and conduct biometrical analyses thereby assisting farmers in making informed decisions (Hamadani and Ganai, 2022). Research has also demonstrated that machine learning techniques can accurately predict sheep breeding values, offering a more effective alternative to conventional strategies (Hamadani et al., 2022). Furthermore, Keshavarzi et al. (2020) conducted a study focusing on the capabilities of a machine learning model in predicting abortion rates in farm animals. Curchoe (2023) presented a conference paper discussing the use of AI to improve in-vitro fertilization (IVF) by enhancing safety, accuracy, and accessibility.

To implement AI in breeding, large volumes of data on genetic and phenotypic traits are required. This data might not be available for all animal farms. On the other hand, AI-driven.

breeding is more prone to reduced genetic diversity. Tools for breeding support are expensive and their use is complicated for a common farmer.

2.10. Mobile phone applications designed for better sheep farming

Traditional sheep farming is plagued by high costs, time constraints, and unreliability. Recent research has focused significantly on the development of AI-based mobile applications and mobile-integrated devices designed to enhance sheep welfare. Given that farms are typically located in rural areas, communication gaps between farmers and veterinarians can lead to financial losses (Barkema et al., 2018; Velde et al., 2018). Mobile-based applications bridge this gap allowing farmers to stay connected with veterinarians and track their animals' health reports. Many of these applications primarily focus on data management from sheep farms, such as the Sheep App, My Sheep Manager, and Ovine Pro (Table 1). Some applications cater to specific needs like the Feed Mix Calculator which helps farmers optimize their animals' feed content, and the Gestimator, an animal pregnancy term calculator. Additionally, devices have been created to work in conjunction with mobile phones, such as the latest LSR-YOLO, a real-time face recognition device (Zhang et al., 2023). This system relies on mobile sheep face recognition system. The system can recognize sheep face with mobile phone camera by matching it to previously taken images of the same sheep. This is a classic example of providing farmers with modern solutions to manage their sheep. Different aspects of sheep farming including pregnancy status, welfare breeding, and vaccination information of sheep can be tracked easily with a faster and accurate face recognition system.

3. Challenges and opportunities

Digitalization has already revolutionized sheep farming and is expected to further enhance animal welfare, productivity, and decision-making in the future. However, while artificial intelligence and machine learning are rapidly advancing, they still face certain challenges. Developing suitable algorithms and validating them remains a challenge

Table 1
Mobile phone applications designed for better herd management, record keeping, feed optimization, and breeding decision support.

Name of mobile application	Developer	Description	Link
Sheep app	Walbro software	This app allows keeping track of individual animal and their vaccination, mating, breeding, and financial information designed to help farming safe, profitable, and more productive.	https://play.google.com/store/apps/details?id=com.tech.sheepapp&hl=en&gl=US&pli=1
My sheep manager – Farming app	Bivatec Ltd.	A farm management app to manage the health, growth and breeding plan designed for more sustainable and efficient farming.	https://play.google.com/store/apps/details?id=com.bivatec.sheep_manager&hl=en&gl=US
OvinoPro	OvinePro	Designed for better sheep handling and herd management. The goal of this app is to abandon the paperwork and save time and farm better with less effort. It even works without internet.	https://play.google.com/store/apps/details?id=br.com.ovinopro.ovino_pro&hl=en&gl=US
Flockwatch by Herdwatch	Herdwatch	This app enables rapid access to breeding, lambing, medicine, weighing records and more. It can also help in monitoring the performance of ewes which then helps with the decision for their breeding in the next season.	https://play.google.com/store/search?q=flockwatch&c=apps
FarmWorks by Shearwell Data	Shearwell data Ltd.	FarmWorks can record the movements, addition, and replacement of animals in the farm. It also records the medical treatment of each animal.	https://play.google.com/store/apps/details?id=com.shearwell.android.farmworks
Easyvet	Appscock technologies	Although this application is for veterinarians to access database for medicines. But it can also be used by farmers to gain knowledge about the medication prescribed by the veterinarians.	https://play.google.com/store/apps/details?id=com.aitrich.Easyvet
Herdboss	In A Day Development	This application is for sheep breeders for recording various details about their flock.	https://play.google.com/store/search?q=herdboss&c=apps
Feed Mix Calculator	H3 Apps	Farmers can find out the optimal feed combination for their animals according to the daily nutrient requirements of their animals.	https://play.google.com/store/apps/details?id=com.h3apps.FeedMix
Gestimator	Ebena Agro Ltd.	Built for farmers for the estimation of animal pregnancy term calculation.	https://play.google.com/store/search?q=Gestimator&c=apps
British Sheep Breeds	Tim Hannah	It is a reference app containing the information of all British sheep breeds and a detailed description of each breed.	https://play.google.com/store/apps/details?id=com.british.sheep.breeds
Sheep Book	EDJE Technologies	This app allow farmers to track the lambing data, breeding information of the ewes, and generate reports. Individual ewe productivity can be monitored and recorded. The semen inventory can be managed with the function of Semen Tank.	https://play.google.com/store/apps/details?id=com.edje.sheepbook
Veterinary handbook	LiveCorp (Australian Livestock Export Corporation)	A comprehensive resource for farmers, veterinarians, and students for detailed information on farm animal health, diseases, and welfare.	https://play.google.com/store/apps/details?id=au.com.livecorp.vethandbook.app

when implementing machine learning. Robust, reliable, and tailored algorithms need to be developed. Solutions for modern farming practices should be adaptable to various sizes and geographical locations and should be user-friendly to encourage adoption by farmers. Additionally, researchers must address ethical and privacy concerns raised by sheep farmers.

Despite the numerous advantages offered by digitalization, such as reduced labor requirements, it's important to acknowledge the crucial role of human intervention. It is crucial to foster strong collaboration between farmers and veterinarians. Veterinary communication and advisory services play a pivotal role in this context, as emphasized by Bard et al. (2019). The absence of effective knowledge dissemination is one of the reasons why sheep farmers worldwide still adhere to traditional farming methods, which come with numerous drawbacks and hinder the industry's overall efficiency. Current digitalization in sheep farming necessitates vigilant monitoring to ensure the well-being of animals. This concern has been raised by Neethirajan (2023), emphasizing that a balanced approach, incorporating both human expertise and digitalization, is the path forward.

Small-scale sheep farmers would likely not benefit from using AI. This is because AI algorithms rely on large datasets for training and validation, especially models that perform predictions. In small sheep farms, they are not always reliable as they may not produce predictable results. Poor quality data can also lead to inaccurate predictions. Moreover, this technology requires significant financial investment in equipment and expertise. Therefore, accessibility to such modernization is the next big challenge. On the other hand, a machine learning model trained in a typical region may not produce the same results as other regions because it has been trained to reproduce results in a specific environment. An example can be taken from AI-based health monitoring systems. These systems rely on collecting various types of data such as feeding behaviours, activity level, temperature, heart rate, and most importantly, environmental conditions. Different environmental conditions can affect the predictability of these systems. These include temperature, humidity levels, precipitation patterns, seasonal changes, geographical location, elevation, and terrain characteristics. Therefore, widespread adaptability is a challenge. Several AI models utilize GPS and other sensors, necessitating high speed internet connectivity such as 5G. Environmental factors like weather or terrain can also affect such systems.

Newly emerging AI-based models are being applied on different animals including sheep, cattle, horses, poultry, pigs, and goats. There is a need to perform optimization of the parameters of existing models made for one type of animal (e.g. cattle) to accommodate a different animal (e.g. sheep). To make precision livestock farming applicable on a large scale in farming operations, the integration of computer modelling with precision farming practices becomes essential (Tedeschi et al., 2021). Overall, AI developments for sheep farming have successfully addressed many previous challenges and are poised to provide additional solutions for sustainable sheep farming. The current concerns related to data quality, animal welfare, cost, environmental adaptability, and reliability of these systems need to be addressed with research, development, and collaboration between technologists, farmers, and animal welfare experts.

Future research endeavors based on artificial intelligence are diverse. Multi-modal data sources like satellite imagery, weather data, and genomic information can be integrated with on-farm sensor data. This would boost the predictive capability of AI models across domains like environmental management, disease prediction, and genetic selection. Although the goal of using AI in sheep farming is to increase productivity, future research should also investigate the ethics of using AI in sheep farming to ensure their ethical treatment. One important research direction is predictive health management using AI. To reduce dependence on antibiotics and improve overall farm health, early disease detection can be achieved with the development of advanced predictive models.

Further research should also see how AI can help sheep farming in changing environmental conditions due to climate change. In this regard, specific focus can be given to adjusting feeding strategies, resource use optimization, and heat stress management. Current AI tools are complex to use. Research should focus on making these tools user-friendly, improving ease of adoption. Overall, the use of digitalization and AI in sheep farming presents a vast and promising frontier, with abundant opportunities for groundbreaking research and innovation.

4. Conclusion

Digitalization has become ubiquitous across all aspects of life, and Artificial Intelligence (AI) aims to make computers capable of understanding, while machine learning empowers computers to make decisions without explicit programming. In the realm of sheep farming, the application of AI-driven digitalization has already proven to be a boon for both sheep farmers and veterinarians, contributing to the sustainability of sheep farming. It has ushered in enhanced sheep management through advanced counting systems, improved disease detection and prevention, precision feeding, anomaly detection, behaviour control, and more. The utilization of AI in sheep farming holds immense potential as it boosts farming efficiency, leading to increased yields. Some of the challenges faced during the implementation of AI technologies in sheep farming include high cost, need for big data, possibility for inaccurate predictions, ethical considerations, problems in adaptability to a new environment, and complexity. These multifaceted challenges necessitate cross-disciplinary collaboration among veterinarians, computer scientists, animal behaviorists, and agricultural engineers. Through such collaboration, future research holds the promise of significantly advancing the efficiency and sustainability of sheep farming through innovative applications of digitalization and AI.

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Muhammad Furqan Arshad: Writing – original draft. **Antonio Varcasia:** Supervision, Writing – review & editing. **Maria Francesca Sini:** Writing – review & editing. **Fahad Ahmed:** Writing – review & editing. **Giovanni Lai:** Writing – review & editing. **Marta Polinas:** Writing – review & editing. **Elisabetta Antuofermo:** Writing – review & editing. **Claudia Tamponi:** Writing – review & editing. **Raffaella Cocco:** Writing – review & editing. **Andrea Corda:** Writing – review & editing. **Maria Luisa Pinna Parpaglia:** Writing – review & editing.

Declaration of competing interest

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

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