BF-1698
[1-6]

RESEARCH ARTICLE Indian Journal of Animal Research

Application of Artificial Intelligence in Monitoring of Animal Health and Welfare

Ahmad Ali AlZubi[1], Maha Al-Zu'bi[2]

10.18805/IJAR.BF-1698

ABSTRACT

Background: With the advent of AI technology, great strides have been made in the realm of animal healthcare. This article delves into the numerous uses of AI in veterinary medicine and demonstrates its revolutionary potential in the field. Artificial intelligence (AI) algorithms have shown impressive skills in illness detection, using medical imaging analysis to help veterinarians discover and categorise diseases with greater accuracy and efficiency. Furthermore, predictive analytics algorithms use various data sources, such as electronic health records and genetic profiles, to recognise trends and forecast illness outbreaks, allowing veterinarians to remotely monitor vital signs and act swiftly paving the way for preventative measures and individualised treatment.

Methods: The purpose of this article is to offer a synopsis of the many ways in which artificial intelligence (AI) is being used to improve the health and well-being of animals. Understanding the effects of AI in animal healthcare and setting the stage for its further development will be accomplished via an examination of the present state of the subject.

Result: It is evident that through mountains of data from studies and clinical trials, AI is helping to speed up the discovery of novel treatments and improve the understanding of animal health. A responsible and useful application of AI in animal healthcare requires the establishment of ethical concerns, data protection and regulatory frameworks.

Key words: Animal healthcare, Artificial intelligence (AI), Precision livestock, Remote monitoring.

INTRODUCTION

Significant progress has been made in animal healthcare as a result of the use of artificial intelligence (AI) technology in recent years. The capacity of AI to go through mountains of data in search of trends suggests it might revolutionise veterinary care and help in safeguarding the well-being of animals, mitigating disease outbreaks and optimizing livestock management, thereby contributing to the sustainable coexistence of humans and animals. AI has emerged as a promising tool, offering unparalleled capabilities in data analysis, pattern recognition and real-time monitoring.

Recent research has shown that "precision livestock farming" is utilizing AI-based technology to improve cattle welfare and productivity where sensors, cameras and data analytics, are being used by farmers to monitor their livestock's feeding habits, behavior, fertility and the spread of illnesses (Bonicelli *et al*., 2021; Ma, 2021). However, there is limited knowledge about the use of artificial intelligence in veterinary science, which deals with animal diseases, treatment and management. This paper provides a brief overview of how AI is impacting animal management methods and techniques. However, as with any new methodology, the application of AI also comes with challenges. It is important to consider the challenges faced in its implementation and the potential risks associated with it. This paper provides a comprehensive examination of the strengths, limitations, methodologies and challenges associated with the application of AI in the monitoring of animal health and welfare.

Disease diagnosis, predictive analytics, therapy optimization, remote monitoring, behavior analysis and data-driven research are just a few examples of how artificial intelligence (AI) is being employed in animal healthcare (Scott, 2021). By utilizing algorithms and machine learning methods (Ma, 2021; Yoo *et al*., 2022), AI has demonstrated potential for improved decision-making, enhanced treatment plans and personalized care for animals. A brief overview of research which is listed under the following subheadings related to various AI applications.

[1]Department of Computer Science, Community College, King Saud University, Riyadh, Saudi Arabia.
[2]Department of Planning and Landscape, School of Architecture, University of Calgary, Calgary, Alberta, Canada.

Corresponding Author: Ahmad Ali AlZubi, Department of Computer Science, Community College, King Saud University, Riyadh, Saudi Arabia. Email: aalzubi@ksu.edu.sa
ORCHID ID: https://orcid.org/0000-0001-8477-8319; https://orcid.org/0000-0001-9810-0103.

How to cite this article: AlZubi, A.A. and Al-Zu'bi, M. (2023). Application of Artificial Intelligence in Monitoring of Animal Health and Welfare. Indian Journal of Animal Research.
doi: 10.18805/IJAR.BF-1698.

Submitted: 11-09-2023 **Accepted:** 14-10-2023 **Online:** 08-11-2023

Early detection of disease

AI-powered monitoring systems can analyze large amounts of data with high precision, detecting health issues or irregularities in animal behavior early on. This technologyreduces the workload for farmers and veterinarians. The most successful machine learning (ML) applications diagnose diseases using medical imaging data and deep learning (Scott, 2021). X-rays, CT scans and MRIs have been used to create AI-powered algorithms that accurately analyze medical images. This technology helps veterinarians diagnose and categorize illnesses promptly and precisely (Yoo *et al*., 2022). Ma (2021) developed an AI module for remotely measuring deep body temperature in cattle using environmental data and infrared images. The horn was found to be the most reliable indicator of core temperature, making it a valuable parameter for early anomaly detection and remote monitoring.

Real-time monitoring and behavioral analysis

Real-time animal monitoring with AI-based analytics can help improve animal welfare and save lives. Remote monitoring allows veterinarians to spot early indicators of distress and intervene quickly. Various systems, such as FMD BioPortal, a web-based platform for sharing and analyzing foot-and-mouth disease (FMD) (Perez *et al*., 2009) and Cyber-physical system (CPS) using IoT sensors (Dineva *et al*., 2021), have been proposed to track animal health, behavior and development. Unlike wearable sensors that may pose challenges, non-invasive methods like video analysis using deep-learning technology can effectively monitor cattle behavior in real time. These systems can identify changes in animal behavior that may signal discomfort, stress, or sickness (Shahinfar *et al*., 2021; Cheng, 2019).

Predictive analytics

AI can predict disease outbreaks and potential health issues by analyzing historical data and identifying patterns, helping farmers and authorities take proactive measures to prevent or mitigate these issues. Electronic health records, genetic information and environmental variables are just some of the data sources that predictive analytics algorithms use to make predictions about disease outbreaks (Yoo *et al*., 2022; Wang *et al*., 2021). In addition, capturing interactions between animals and their environment can predict animal diseases. Budgaga *et al*. (2016) utilized Discrete event simulations (DES) making use of abundant computing resources from public and private clouds. They created predictive models with real-time feedback, enhancing accuracy through dimensionality reduction and ensemble methods. This user-friendly interface allows modellers and epidemiologists to observe projected disease outcomes and make informed decisions for animal health management.

Treatment optimisation and data-driven decision making

Another area where AI shows promise is in treatment optimisation. Veterinarians are given a helping hand by AI-powered data-driven decision support systems when formulating individualised treatment plans for their patients by taking into account the animal's medical history, genetics and responsiveness to various medications. This optimisation aids in the selection of suitable drugs, the establishment of suitable dose levels and the assessment of the effectiveness of various treatment methods (Monaco *et al*., 2021; Bonicelli *et al*., 2021). AI enables data-driven decision-making in animal husbandry, optimizing feed, resource allocation and breeding programs. This can lead to increased productivity and resource efficiency. Yongqiang *et al*. (2019) developed an optimisation and improvement plan to address the drawbacks of current sheep housing facilities through the integration of disciplines such as automated feeding, precision feeding, automatic door closure, photographic weighing, UAV (Unmanned Aerial Vehicle) sheep farm patrol and Herd Behaviour Image Analysis, *etc*.

Applying artificial intelligence (AI) in animal welfare and health has the potential to bring significant benefits, but it also faces several weaknesses and challenges. The most important being challenge is to acquire datasets due to privacy concerns, limited resources and variations in animal species and conditions. Such data limitations can add a subsequent amount of bias (Norori *et al*., 2021). In addition, the use of AI in animal welfare raises ethical questions, such as whether AI can adequately replace human compassion and understanding in caring for animals (Coghlan and Parke, 2023). It is essential to ensure that AI is used as a tool to assist humans rather than replace them entirely. Moreover, the technical complication known as the "black box" is of major concern where the AI models appear to be challenging to interpret for humans in decision-making processes. Also, the complexity of the algorithm's structure gives rise to a lack of transparency due to its reliance on geometric relationships that humans cannot visualize easily (Bathaee, 2017). Above all, animal behaviour is highly complex and often difficult to predict accurately. While AI can analyze patterns in data, understanding the motivations and emotions of animals remains a significant challenge. Yet, the techniques and methodologies are being regularly updated to overcome these limitations. The next section briefly describes the methodology employed in developing algorithm development.

MATERIALS AND METHODS

Using AI for animal health monitoring involves collecting data from sensors, cameras and wearables to create a comprehensive dataset of physiological and behavioural characteristics. This data is then analyzed using AI techniques to create predictive models and algorithms that can detect deviations from normal behaviour and provide real-time alerts to caretakers or veterinarians. The steps involved in the methodology are described below.

Data collection

Behavioral traits of animals are typically studied by collecting real-time observational data using camera systems (Cho and Kim, 2023). Surveillance cameras are strategically set up across a farm to capture video footage of the animals. The cameras should have appropriate resolution, frame rate and coverage to capture relevant behaviours and health indicators. After acquiring data there are two main phases, the preprocessing phase and the training and validation phase.

Data preprocessing

Annotation and labelling

The data obtained are used to extract video frames. More precise variations can be captured by extracting images at a rate of 15 frames per second (Fuentes *et al*., 2023). Optionally, filtering of frames is done to remove noise or irrelevant content. Noise removal plays a critical role in enhancing the quality of data. This step involves the elimination of unwanted artefacts or disturbances that may obscure relevant information in the images. For, example, a study by Bo *et al*. (2022) developed a system to monitor pigs using infrared cameras with hazy spots. The system included a data collector, preprocessor and detector to identify pigs. The preprocessor utilized advanced techniques like GAN models and improved pig detection accuracy with minimal additional processing time. These video frames are then annotated with labels for various animal behaviors and health indicators. This can be done manually or using computer vision techniques (Ravbar *et al*., 2019). Annotation in the preprocessing of images using AI is essential because it provides the necessary labelled data for training and evaluating AI models (Maayan, 2022). It adds semantic context to images, aids in feature extraction and enables AI systems to understand and interpret visual information accurately, making them useful in a wide range of applications, from object recognition to medical diagnostics and more (Rebinth and Kumar, 2019).

Feature extraction

Relevant features are then extracted from the video frames. These may include object detection by identifying and tracking individual animals or by posture and behavior analysis to analyze posture, movement, feeding behavior, social interactions and abnormal behaviors. Health indicators can be identified by detecting signs of illness, injury, lameness, or distress. Here, it is important to ensure the absence of observers near animals during the acquisition of activity images to prevent any interference with the animal's natural behaviours (Cho and Kim, 2023). The extracted features are processed by developing machine learning or deep learning algorithms to make predictions. For this, convolutional neural networks (CNNs) for image analysis and recurrent neural networks (RNNs) or transformers for temporal data analysis can be used (Valletta *et al*., 2017).

Training and validation

The annotated dataset is then split into training, validation and test sets. The algorithm developed is then trained and fine-tuned using the validation set. Machine learning creates adaptable computer programs that use specialized algorithms to train and forecast data. Fig 1 shows an AI-based system that integrates with IoT devices to analyze animal health.

The machine learning models can be categorised into two groups: supervised and unsupervised learning. In a supervised learning system, both the input and the expected output data are explicitly supplied. Input and output data are labelled for categorization, providing a learning foundation for future data processing.

Supervised learning tasks may be divided into two categories: regression and classification competitions. In a regression issue, the outcome is a real or continuous value like "salary" or "weight,". Fig 1 shows an AI-based system that integrates with IoT devices to analyze animal health.

RESULTS AND DISCUSSION

In the present study, the sklearn module, which stands for scikit-learn (a popular machine-learning library for Python, was used. To train the dataset the 'animal-h' dataset is imported which is conveniently included as a built-in part of the sklearn module. This dataset is structured as a tabular compilation of information related to variations in animal vital signs. It serves as the foundation for training the machine learning model, enabling it to learn and understand the underlying patterns and relationships within the data.

Through this training process, the model becomes capable of making accurate predictions and inferences based on the input features, ultimately helping to monitor and analyze animal health effectively.

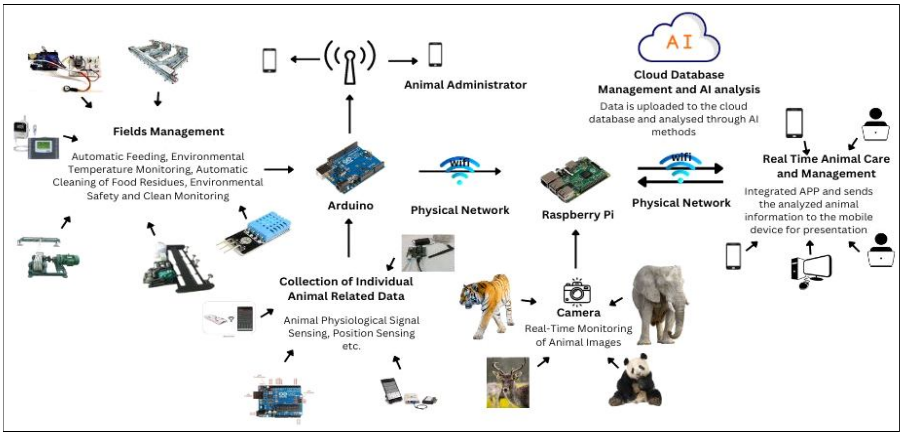

Fig 1: Extracting information from massive data to monitor animal health and better rationalise treatments.

With the help of the train test split operation, the dataset is further separated into test and training samples. The train-test split operation is a crucial step in machine learning. It allows us to divide the dataset into two subsets: the training set, which is used to train the machine learning model and the test set, which is used to evaluate the model's performance on unseen data. In this process, we typically use the 'X' prefix for variables representing feature values (input data) and the 'y' prefix for variables representing target or goal values (output data).

Mathematically, we can represent this operation as follows: Let X be the feature matrix (input data) and y be the target vector (output data). We can split these into training (X_train, y_train) and testing (X_test, y_test) sets as follows:

X_train, X_test, y_train, y_test = Train_test_split (X, y, test_size=0.2, random_state=42).

Here, the dataset was split into training and test data, typically using a 67:33 split ratio. This random splitting allows the use of any machine learning algorithm for prediction.

Dataset validation

To forecast the health of an animal for whom the dimensions of a numpy array named 'n' containing vital data have been acquired. Here, a prediction method is used, which takes this array as an argument and outputs the projected target value. Here, the target value is zero which corresponds to good health. After using the prediction method to estimate the animal's health, a test score is calculated to evaluate the accuracy of the predictions. This score is determined by comparing the number of correct predictions (*i.e.*, predictions that match the actual health status) to the total number of predictions made. This reflects how well the model performs in predicting the animal's health status.

The Fig 2 and 3 shows all the analytic steps from data cleaning and processing to missing value analysis to exploratory data analysis to model creation and assessment, In the end, the predictions about the illness were made by a machine-learning system where we obtained mixed results. Some of the following conclusions concerning illness forecasting may be drawn from this.

Prediction accuracy

The ability to make accurate predictions about an animal's health can have profound implications for veterinary care,livestock management, wildlife conservation and even early disease detection. Prediction accuracy, often measured as a percentage which quantifies how well a model's predictions align with actual outcomes and serves as a metric for

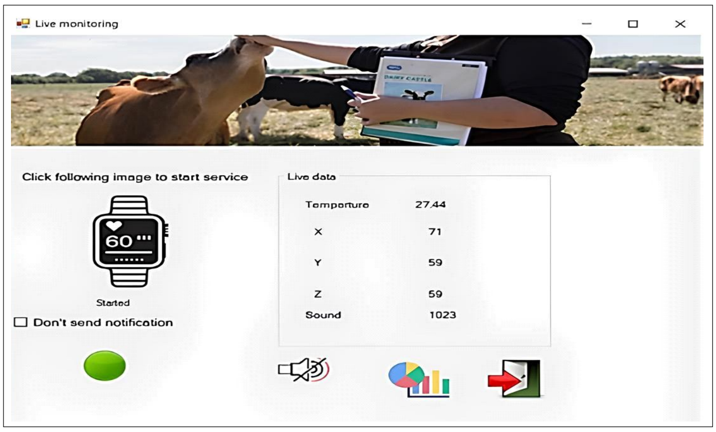

Fig 2: Live data monitoring.

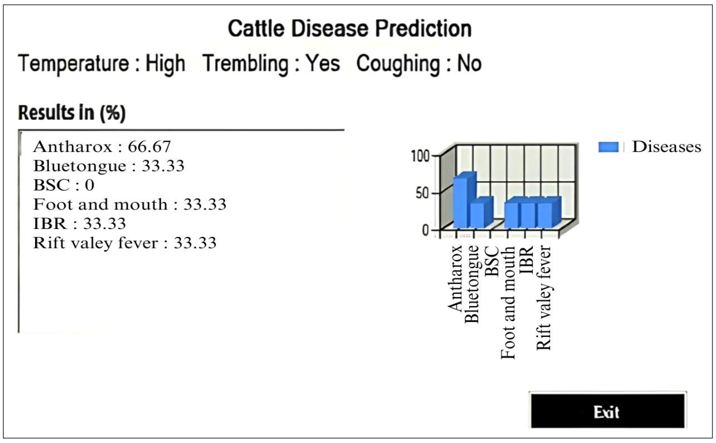

Fig 3: Report of the disease predicted using artificial intelligence.

evaluating the model's performance. A high accuracy rate indicates that the model is making correct predictions, while a lower accuracy suggests room for improvement. As high as 100% accuracy has been achieved by various researchers in classifying diseased and undiseased animals (Neethirajan, 2020; Hwang *et al*., 2022; Zhou *et al*., 2022). The detailed overview provided above indicates that AI is being used to monitor animals and estimate the likelihood of detecting diseases. While not widely adopted, this approach helps in planning future monitoring programs by identifying the most promising samples or cases to target. By doing so, it maximizes the use of resources and laboratory capacity. Disease research across various organisms, including animals and plants, has utilized metadata related to biological samples or cases, such as location, host type/age and more.

Although AI has the potential to improve animal welfare and predict diseases, the threats associated with computer-based programs still persist, which calls for caution. One major concern is protecting sensitive data from cyberattacks and misuse. To ensure smooth operation of technology-dependent systems, strong security measures are necessary (Neethirajan, 2023). Additionally, it is important to bridge the knowledge gap between farmers and technology by providing effective training for the successful implementation of AI systems (Moreira *et al*., 2023). The cost of using AI-powered equipment is another obstacle for farmers, as it involves significant initial expenses for purchasing hardware, software and training staff (Eli-Chukwu, 2019). Besides, the adoption of AI may create economic disparities in the agriculture sector, as smaller farmers may struggle to invest in AI technologies (Rotz *et al*., 2019). An overreliance on AI systems could lead to complacency in animal care and decision-making, potentially overlooking the importance of human expertise. Yet, AI has the ability to quickly identify signs of distress, disease, or injury in animals aiding in the early detection and control of livestock diseases. Furthermore, AI-generated insights can promote sustainable farming practices by minimizing resource usage and environmental impact.

CONCLUSION

These fields are able to progress quickly because they make use of artificial intelligence techniques (*e.g*., machine learning, expert systems, analytical technologies) in conjunction with the collection of enormous and complicated data. The collection of data does not necessarily lead to an advance in understanding, thus it is important to distinguish between big data and AI as separate trends. However, the more meaningful findings may be gained from AI applications, the more plentiful and representative the data are of working notions and hypotheses. There must be a national reflection on the ethical, deontological and legal foundations of data ownership, storage, management, sharing and interoperability. Accelerating the growth of these fields is the application of artificial intelligence techniques (*e.g*., machine learning, expert systems, analytical technologies). The collection of data does not necessarily lead to an advance in understanding, thus it is important to distinguish between big data and AI as separate trends. However, the more meaningful findings may be gained from AI applications, the more plentiful and representative the data are of working notions and hypotheses. There must be a national reflection on the ethical, deontological and legal foundations of data ownership, storage, management, sharing and interoperability.

Despite these risks and ethical considerations, there is no denying that AI is already being used in veterinary science. For example, AI-powered diagnostic tools are already being used to help identify and treat conditions in animals. Additionally, AI is being used to monitor the health and well-being of animals in real-time, which can help prevent health issues before they become serious. There is a need to construct regulatory frameworks, set ethical rules and protect patient data before we can use it in any meaningful way. Instead of being perceived as a threat to the livelihood of veterinarians, AI should be seen as a useful tool that may help them better serve their patients (Yongqiang *et al*., 2019; Roth *et al*., 2018).

ACKNOWLEDGEMENT

The authors would like to thank the editors and reviewers for their review and recommendations and also to extend their thanks to King Saud University for funding this work through the Researchers Supporting Project (RSP2023R395), King Saud University, Riyadh, Saudi Arabia.

Funding statement

This work was supported by the Researchers Supporting Project (RSP2023R395), King Saud University, Riyadh, Saudi Arabia.

Authors' contributions

The author Ahmad Ali Alzubi was responsible for designing the paper as well as preparing the original draft. The collection of research papers and analysis was done by Maha Al-Zu'bi.

Declaration of conflict of interest

Authors declare that they have no conflict of interest.

Data availability statement

Not applicable.

Declarations

Author(s) declare that all works are original and this manuscript has not been published in any other journal.

REFERENCES

Bathaee, Y. (2017). The artificial intelligence black box and the failure of intent and causation. Harv. JL and Tech. 31, 889.

Bo, Z., Atif, O., Lee, J., Park, D. and Chung, Y. (2022). GAN-based video denoising with attention mechanism for field-applicable pig detection system. Sensors. 22(10): 3917. MDPI AG. Retrieved from http://dx.doi.org/10.3390/s22103917.

Bonicelli, L., Trachtman, A.R., Rosamilia, A., Liuzzo, G., Hattab, J., Mira Alcaraz, E., Del Negro, E., Vincenzi, S., Capobianco, D.A., Calderara, S. and Marruchella, G. (2021). Training convolutional neural networks to score pneumonia in slaughtered pigs. Animals. 11(11): 3290. MDPI AG. Retrieved from http://dx.doi.org/10.3390/ani11113290 doi:10.3390/ani11113290.

Budgaga, W., Malensek, M., Pallickara, S., Harvey, N.E. Breidt, F.J. (2016). Predictive analytics using statistical, learning and ensemble methods to support real-time exploration of discrete event simulations. Future Generation Computer Systems. 56: 360-374.

Cheng, Y.H. (2019). A Development Architecture for the Intelligent Animal Care and Management System Based on the Internet of Things and Artificial Intelligence. In 2019 International Conference on Artificial Intelligence in Information and Communication (ICAIIC) (pp. 78-81). IEEE. doi: 10.1109/ICAIIC.2019.8669015.

Cho, Y. and Kim, J. (2023). AI-based intelligent monitoring system for estrus prediction in the livestock industry. Applied Sciences. 13(4): 2442. MDPI AG. Retrieved from http://dx.doi.org/10.3390/app13042442.

Coghlan, S. and Parker, C. (2023). Harm to nonhuman animals from AI: A systematic account and framework. Philosophy and Technology. 36(2): 25. https://doi.org/10.1007/s13347-023-00627-6.

Dineva, K., Parvanov, D., Atanasova, T., Mateeva, G., Petrov, P. and Kostadinov, G. (2021). Towards CPS/IoT system for livestock smart farm monitoring. In 2021 International Conference Automatics and Informatics (ICAI). 252-255. IEEE. doi: 10.1109/ICAI52893.2021.9639460.

Eli-Chukwu, N.C. (2019). Applications of artificial intelligence in agriculture: A review. Engineering, Technology and Applied Science Research. 9(4): 4377-4383.

Fuentes, A., Han, S., Nasir, M. F., Park, J., Yoon, S. and Park, D.S. (2023). Multiview monitoring of individual cattle behavior based on action recognition in closed barns using deep learning. Animals. 13(12): 2020. https://doi.org/10.3390/ani13122020.

Hwang, S., Shin, H.K., Park, J.M., Kwon, B. and Kang, M.G. (2022). Classification of dog skin diseases using deep learning with images captured from multispectral imaging device. Molecular and Cellular Toxicology. 18(3): 299-309.

Ma, S., Yao, Q., Masuda, T., Higaki, S., Yoshioka, K., Arai, S., Takamatsu, S. and Itoh, T. (2021). Development of noncontact body temperature monitoring and prediction system for livestock cattle. IEEE Sensors Journal. 21(7): 9367-9376. doi: 10.1109/JSEN.2021.3056112.

Maayan, G.D. (2022) The Role of Image Annotation in Machine Learning Engineering. https://www.computer.org/publications/tech-news/trends/image-annotation-in-machine-learning.

Monaco, A., Pantaleo, E., Amoroso, N., Lacalamita, A., Giudice, C.L., Fonzino, A., Fosso, B., Picardi, E., Tangaro, S., Pesole, G. and Bellotti, R. (2021). A primer on machine learning techniques for genomic applications. Computational and Structural Biotechnology Journal. 19: 4345-4359. doi: 10.1016/j.csbj.2021.07.021.

Moreira, L.F.R., Moreira, R., Travençolo, B.A.N. and Backes, A.R. (2023). An artificial intelligence-as-a-service architecture for deep learning model embodiment on low-cost devices: A case study of COVID-19 diagnosis. Applied Soft Computing. 134: 110014. doi: 10.1016/j.asoc.2023.110014.

Neethirajan, S. (2020). The role of sensors, big data and machine learning in modern animal farming. Sensing and Bio-Sensing Research. 29: 100367. https://doi.org/10.1016/j.sbsr.2020.100367.

Neethirajan, S. (2023). The significance and ethics of digital livestock farming. Agri Engineering. 5(1): 488-505.

Norori, N., Hu, Q., Aellen, F.M., Faraci, F.D. and Tzovara, A. (2021). Addressing bias in big data and AI for health care: A call for open science. Patterns (New York, N.Y.). 2(10): 100347. https://doi.org/10.1016/j.patter.2021.100347.

Perez, A.M., Zeng, D., Tseng, C.J., Chen, H., Whedbee, Z., Paton, D. and Thurmond, M.C. (2009). A web-based system for near real-time surveillance and space-time cluster analysis of foot-and-mouth disease and other animal diseases. Preventive Veterinary Medicine. 91(1): 39-45.

Ravbar, P., Branson, K. and Simpson, J.H. (2019). An automatic behavior recognition system classifies animal behaviors using movements and their temporal context. Journal of Neuroscience Methods. 326: 108352. https://doi.org/10.1016/j.jneumeth.2019.108352.

Rebinth, A. and Kumar, S.M. (2019). Importance of manual image annotation tools and free datasets for medical research. Journal of Advanced Research in Dynamical and Control Systems. 10(5): 1880-1885.

Roth, J.A., Battegay, M., Juchler, F., Vogt, J.E. and Widmer, A.F. (2018). Introduction to machine learning in digital healthcare epidemiology. Infection Control and Hospital Epidemiology. 39(12): 1457-1462. doi:10.1017/ice.2018.265.

Rotz, S., Duncan, E., Small, M., Botschner, J., Dara, R., Mosby, I., Reed, M. and Fraser, E.D. (2019). The politics of digital agricultural technologies: A preliminary review. Sociologia Ruralis. 59(2): 203-229.

Scott, I.A. (2021). Demystifying machine learning: A primer for physicians. Internal Medicine Journal. 51(9): 1388-1400. doi:10.1111/imj.15200.

Shahinfar, S., Khansefid, M., Haile-Mariam, M. and Pryce, J.E. (2021). Machine learning approaches for the prediction of lameness in dairy cows. Animal. 15(11): 100391. doi: 10.1016/j.animal.2021.100391.

Valletta, J.J., Torney, C., Kings, M., Thornton, A. and Madden, J. (2017). Applications of machine learning in animal behaviour studies. Animal Behaviour. 124: 203-220.

Wang, M.W.H., Goodman, J.M. and Allen, T.E.H. (2021). Machine learning in predictive toxicology: Recent applications and future directions for classification models. Chemical Research in Toxicology. 34(2): 217-239. doi: 10.1021/acs.chemrestox.0c00316.

Yongqiang, C.H.E.N., Shaofang, L.I., Hongmei, L., Pin, T. and Yilin, C.H.E.N. (2019). Application of intelligent technology in animal husbandry and aquaculture industry. In 2019 14th International Conference on Computer Science and Education (ICCSE). 335-339. IEEE. doi: 10.1109/ICCSE. 2019. 8845527.

Yoo, D.S., Song, Y.H., Choi, D.W., Lim, J.S., Lee, K. and Kang, T. (2022). Machine learning driven dynamic risk prediction for highly pathogenic avian influenza at poultry farms in Republic of Korea: Daily risk estimation for individual premises. Transboundary and Emerging Diseases. 69(5): 2667-2681.

Zhou, X., Xu, C., Wang, H., Xu, W., Zhao, Z., Chen, M., Jia, B. and Huang, B. (2022). The early prediction of common disorders in dairy cows monitored by automatic systems with machine learning algorithms. Animals. 12(10): 1251. https://doi.org/10.3390/ani12101251.