Animal Behavioural Ecology Research Through AI: A Concise Overview of Recent Progress

Raj Rajeshwar Malinda[#, *]

[#]Graduate School of Information Science, University of Hyogo, Japan

[*]Correspondence: contact@rrmalinda.com

Abstract

Artificial intelligence (AI) is predominantly most discussed topic of recent times in scientific research. In an ecological context, animal behaviour is documented complex and dynamic, and analysis often requiring substantial investment of manual efforts and rigorous tasks. With the integration of emerging technologies, such as AI, the tools and techniques available to study animal behaviour have broadened and deepened the research domain. AI integration has accelerated the automation of tasks performance in behavioural classification, detection, tracking, pose estimation and action recognition in animals. In this paper, I concisely review the current progress in AI methods applied to understand animal behaviour, and discuss their potential impact on ecological research.

Keywords

Artificial intelligence, Machine learning, Deep learning, Visual ecology, Animal behaviour

AI into animal behavioural ecological research

Artificial intelligence (popularly known as AI), machine learning (ML), and deep learning (DL), in recent times, without any doubt, are the most discussed and explored tools compared to any others in both scientific and non-scientific communities [1], [2], [3], and overlap with the interests of almost all core disciplines such as biological [3], [4], chemical [5], and physical sciences [6]. AI further extends into medicine [7], imaging [8], drug development [9], as well as ecological, and wildlife conservation sciences [10], [11], [12], [13], [14], [15]. It is, therefore, worth mentioning that, robust use of AI in the diagnosis of pathological conditions such as cancer, and other rare diseases is encouraged [16].

In a broader context of ecology, researchers investigate a wide spectrum of questions, ranging from theoretical understanding to applied ecological processes [13], which are further divided into various lines of research, such as population, ecosystem, physiology, conservation, and behavioural ecology. In specific context of animal behaviour, various aspects, including evolutionary patterns, social structure and responses, foraging, and the effects analysis of environmental factors on animals, among others, are studies [17], [18], [19].

In the conceptual framework of AI, a transformative technology, it has further evolved into ML, and DL [3], [13]. Therefore, in terminological terms, ML and DL come under the umbrella overview of AI. In brief, ML applications (often referred to as algorithms) help to predict the outcomes of specific tasks based on trained datasets. However, DL has further advanced into a specialized tool for performative tasks, using neural networks to process complex datasets. Artificial neural networks (ANNs), convolution neural networks (CNNs), recurrent neural networks (RNNs), long short-term memory networks (LSTM) and generative adversarial networks (GANs) are specific mechanisms of DL's processing capabilities. In a combined boarder overview, the use of AI technologies in ecological research can primarily enhance tasks productivity, although often comes with challenges as well [12], [20].

In the dynamic scenarios of emerging technologies adaptation, behavioural analysis whether focused on an individual animal or a group, consider various approaches and their associated behavioural phenomena, which offer significant insights into the ecological and behavioural contexts of animals [21]. In the changing landscape of animal behavioural analysis, recent work shows the overlap and integration of AI, as illustrated in graphical abstract. Growing interests in AI, has also accelerated ecological research in animal behaviour, conceptually broadening and deepening the fundamental understanding of the subject [10], [11], [14], [22], [23], [24], [25], [26], [27], [28], [29], [30]. Animal behavioural analysis and the associated information are far more complex and dynamic in nature, and therefore require multi-dimensional approaches to study in an ecological context [18], [19]. AI accelerated key progress in animal behavioural studies, particularly in automated detection, tracking, post estimation, behavioural classification, camouflage object detection (COD) from videos and images, both in controlled experimental conditions, and in real-time scenarios in the wild [12], [30], [31], [32], [33], [34].

In this article, I discuss and highlight the recent progress in animal behavioural research by leveraging the emerging technologies of AI. Given the scope and nature of the topic, a concise overview is provided, focusing on recent studies of animal behaviour analysis, methods integration, and advancements using artificial intelligence, machine and deep learning techniques, particularly in animal behavioural classification, pose estimation, tracking and camouflage object detection.

Automated animal behavioural analysis

Tracking and pose-estimation

Animal behaviour in classical settings, is more complex and dynamic, with various approaches adopted to study it [17], [19], [35], among others, for example, detection, tracking, pose-estimation and classification using computer vision [36], [37], [38], with specific interests to aquatic and terrestrial animals [39], [40], [41], [42], [43]. Computer vision, however, involves a combination of specialized tools and techniques to analyze animal behavioural through images and videos processing tasks. It is considered a powerful method employed by ecological researchers [32], [42], [44]. Recent advancements have demonstrated tremendous progress in computer vision techniques, and numerous tools are, now, available that are specific to different species of both aquatic and terrestrial animals [42], [44]. These tools can be applied directly in the wild or under controlled laboratory conditions, using recorded videos and images, and in real-time scenarios. Behavioural analysis through videos and images for tasks like detection, tracking and pose estimation, with the integration of AI, can significantly advance computer vision research in animal behaviour [27], [32], [39], [41], [44]. Although, the field of computer vision has made incredible strides in enhancing the performance of behavioural tasks analysis, yet only a limited number of software offer automated or substantial integration of advanced intelligence techniques, such as machine and deep learning pipelines. It is notable, most of computer vision tools, regardless of their behavioural task performance, require a highly powerful hardware setup, and therefore increase the cost associated [31], [45], [46].

As mentioned earlier, due to the scope of this paper, I focus on highlighting and discussing some of recent studies, focused on computer vision tools integrated with artificial intelligence approaches, including ML and DL. Chen et al., developed a ML-based pipeline for behavioural task performance called AlphaTracker, that facilitates the analysis of multiple animals' behaviour [47]. This system further incorporates pose-estimation with unsupervised ML algorithms, such as clustering, and enable tracking of unmarked animals. Therefore, this pipeline improves the computer vision task with minimal hardware requirements, aiding the understand the socially complex and dynamic behaviour of animals [47]. To further exploration, it is highlighted that use of CNNs-based models for animal behaviour analysis from videos, using top-down or bottom-up convolutional pose estimation in various animals, including mice and flies [28], [48], [49], [50]. Integrating AI methods into computer vision can reduce the laborious tasks, with outputs significantly surpassing those of traditional manual methods [3].

In animals, pose estimation serves as an effective marker for identifying them within complex and cluttered natural environments. In this attempt, Biderman et al., proposed 'Lightning Pose', a semi-supervised method integrated with Bayesian ensembling tools to enhance the analysis in behavioural ecology [51]. To further support, the integration of advanced intelligence tools and techniques in computer vision tasks, it is emphasized that, such pipeline methods can significantly reduce manual labor through automatic segmentation and grouping of repeated action patterns, facilitating the study of animal behaviour. In animal post estimation research, Dunn et al., employed three-dimensional geometric DL-based technique for multi-view pose estimation, and introduced DANNCE, a volumetric convolutional network method, that infers 3D coordinates of freely moving animals [52]. Notably, DANNCE was trained with datasets of over 7 million-frames of rat behaviour (Rat7M), and outperformed standard two-dimensional triangular methods, and further reduced the manual engagement in labelling of datasets, as claimed [52], [53].

With the recent progress of AI, newly developed tools and applications for animal detection, tracking, and pose estimation, either for single or multiple animals, now offer integration of AI advancements [47], [49], [50], [51], [52], [53]. These improvements ease the implementation of traditional methods, and therefore, allowing researchers to exert minimal efforts while benefiting from a more robust and user-friendly interface [3]. However, due to diverse morphological, behavioural, and habitual characteristics of animals, a single software application may not always be effective, or may produce minimal outputs than initially expected, even if it is claimed to be highly efficient in specific scenarios [20]. For example, a newly developed animal tracker integrated with AI may worked effectively in detecting and tracking for animal A, but might be less effective for animal B, due to trained datasets specifically for Animal A. Therefore, it is essential to understand and choose trackers that are specifically suited to the needs of different animals, regardless the integration of the AI or ML tools, and to carefully review the fundamentals of such animal trackers [54]. AI-integrated techniques promise to provide more informative and detailed kinematic profiles of posture and motion across species, including in the wildlife and natural habitat.

Behavioural classification and recognition

To extend, AI integration in animal behavioural analysis, just beyond detection and tracking tasks, several studies have demonstrated significant progress in behavioural classification and action recognition from various-types of videos and images, including camera traps in the wild. Schindler et al., in their study, introduced an end-to-end “action detection” pipeline for camera trap videos, that is considered highly useful in wildlife and conservational studies. Their approach involved segmenting with filters of tracklets using a method called SWIFT [55], to track wildlife animals from videos. This method was further enhanced by integrating the mask-guided action recognition network, called as MAROON [56] which automated and improves the pipeline with more accurate recognition of animals, particularly datasets of deer species, even when multiple animals are present simultaneously [55], [56].

In natural terrestrial habitats, background complexity and the presence of multiple species, are quite often and common challenging problems researchers encounter. Given such conditions, this work was built on spatial-temporal features extraction using three-dimensional CNNs applied to video data. 3D CNNs have been used in neural network-based approaches for animal action classification [48]. It is noted that, DL-based architectures are widely used methods for animal action recognition through pose estimation and tracking features. For example, SLEAP [49], DeepLabCut [50], DenseNet [57], and others software applications leveraging neural network architectures. Furthermore, it is emphasized that, methods for two-dimensional datasets using CNNs architectures have been started nearly a decade ago, however, earlier studies might comparatively limited due to limited outputs, high computational power costs, and scarce recourses [58]. Recently, use of AI has seen a sharp increase in research and applications across all domains, because of inexpensive computational resources distribution, including animal behavioural ecological and conservational research.

Equivalently, in aquatic animals, especially in fish behavioural analysis, AI-based classification has highlighted the used of CNNs, LSTM, and GANs, within deep learning, to detect and classify fish in complex and dynamic underwater natural environment [59], [60]. It is further argued, that, recent DL-based models achieve accuracy comparable to human performance in species classification, not only limited to aquatic habitat, but also in more complex terrestrial environment [55], [56]. Various behavioural aspects of fish, such as movement, feeding, and escaping, can be recognize by DL-based models with greater accuracy than before. However, it is emphasized that, analyzing fish behavioural responses remains challenging due to the complexity of environmental backgrounds, morphological differences within species, and moreover unpredicted movements, among others, and AI-driven approaches are expected to enhance such tasks in the future [59], [60].

In another dimension, various studies suggested that AI-enabled platforms for controlled experimental analysis of animal behaviour, utilizing basic DL backbone architectures, along with various advanced methods, to enable automated behaviour recognition in animals [28], [47], [50]. Several animal behaviour features, including sound, visuals, or both, have been effectively extracted using DL-associated techniques [28]. By refining deep neural network parameters, along with the various algorithms used, real-time animal behaviour classification has been successfully achieved [61]. Furthermore, to map behavioural analysis from 3D action skeletons, a novel unsupervised spectrogram UMAP-based temporal-link embedding method called as SUBTLE, was developed by a team from the Republic of South Korea [62]. This study further highlights the use of temporal-based behavioural embedding for more accurate categorization. Some recently introduced graphical user interface (GUI)-based tools also demonstrate significant progress in AI integration for animal behavioural analysis, with several built upon previously available platforms [47], [49], [50], [62].

Ostuka et al., developed a DL-based framework for animal behaviour classification using animal-borne accelerometers, providing valuable tools for the bio-logging research domain [23]. Another framework, for animal recognition, ASBAR, was introduced for recognition of large animals, specifically in ape behaviour, by integrating a CNNs-based architecture with key point annotations method [63]. Researchers in ecological studies preferer using DL-based intelligence approaches for better performance compared to more conventional ML methods [28], [49], [50], [60], [61]. It is further argued that, DL-based approaches, are more efficient in handling large training datasets, enabling better predictions for unseen data, despite the high computational power required by these DL methods [28], [34], [60], [61].

On the contrary, most AI-based researchers come from the developed world rather than the global south, highlighting the need for powerful computational and other required resources is such studies. However, these arguments emphasize the unequal distribution of resources for AI-based research, and further, the centralized nature of their utilization [64], [65].

Camouflage object detection

Color-dependent patterns elucidate various behavioural phenomena in animals, going beyond adaption and expression in the natural habitat. They also play a dynamic role in survival to the nature, defense against predators, body regulation, signaling associated with the surrounding to make social bonds, and even in evolutionary perspective [66], [67], [68], [69], [70]. The color-associated visual systems that helps animals to match background information, commonly referred to as camouflage, have been a focus point for ecology and evolutionary researchers for decades [69], [70]. As a results, integration of AI tools and techniques, therefore, is indeed becoming increasingly essential in current research scenarios in camouflage object detection.

Natural conditions in the wild, the complexity of backgrounds, and noise interference are among the major challenging tasks in detection of animals. The integration of more advancement intelligence system, such as residual deep neural network combined with genetic algorithms, has gained attentions among researchers [33], [70], [71].

Fennell et al., used a method called “Camouflage Machine” to extract various color-dependent phenotypes in animal associated with conspicuous signals [71]. In this study, they tested a novel approach, to understand the complex phenomena associated with animal camouflage [70], aiming to improve conventional methods for detecting and identifying pattern more realistically in natural environments [71], [72]. This task is often the most challenging in some scenarios, especially when dealing with general camouflage [70]. By using both trichromatic and dichromatic color-dependent vision systems, along with genetic algorithms and deep neural networks, they enhanced the optimization of parameters, achieving reasonable success in the task of animal identification [71], [73]. Such studies not only enhance the fundamental understanding of the core domain but also broaden the horizon by incorporating modern state-of-the-art techniques integrated with advanced AI [3], [70], [71].

Ike et al., proposed a DL-based framework, called Discriminative Context-Aware Network (DiCaNet), which combines ARB-Net and CDB for COD, and therefore, significantly improving the visible sensitivity of detection [72], [74]. Furthermore, a more robust pipeline was employed with additional attention weights used for feature maps in convolution network, focusing on localization and segmentation of the objects. This process effectively modulates evaluation metrics, enhancing camouflage object detection [74].

Wen et al., introduced a method based on DL techniques, utilizing attention-guided edge detection and multi-scale context fusion [75]. Guo et al. 2025, showed Contrastive Learning with Augmented Data (CLAD) to improve, and addressing the significant challenges in COD [76]. In addition, other studies have incorporated informative artificial intelligence along with other intelligence tools and techniques, to effectively enhance the detection of the objects or animals, adding the segmentation to visually complex camouflage scenarios [76], [77], [78]. It is, further, evident that, combining various DL methods, can enhance detection tasks in COD. for example, CNNs combined with ANNs provide more accurate outputs than any standalone deep learning techniques, including LSTMs, in camouflage object detection [78], [79], [80].

Although, Zhang et al., argued the limited availability of real-time datasets, that hinders the improvement of AI models in COD, and, therefore, emphasized the use of generative camouflage images matched to natural scenes and background complexity [81]. Their study demonstrated more effective object detection in camouflage images using generative images. These findings open new avenues for researchers to use synthetic images, and such concepts therefore should not be limited to camouflage object detection only, but also apply to other research domains as well, to improve their AI models and achieve better results [3], [14], [78], [80], [81], [82]. Such studies also highlight the importance of generative AI in ecological research [81], [82]. Interestingly, a comprehensive analysis by Xiao et al., pointed out that, COD research has sharply shifted the paradigm from traditional to deep learning methods, and notably, traditional approaches to study COD have almost vanished over the last half-decade [72]. These findings further support the idea of improving COD using AI models, and further experimenting exclusively with AI-dependent models, while also raising concerns about the potential disappearance of fundamental techniques [72], [80], [82].

Conclusion

To summarize the recent developments within the field of animal behavioural ecology, it is evident that, AI techniques, particularly DL, have made incredible progress. Researchers are continuously improving existing AI models in terms of accuracy, and predictions, consistent with other research fields [3], [28], [60], [79], [83]. The integration of AI tools further enhances productivity and precision, and further reducing the need for manual annotations in animal behavioural classification, detection, tracking and pose estimation, among others. While automated tasks using AI in animal behavioural studies, have significantly progressed, however, still space remains for the potential use of AI. In the wild, animals live in complex and noisy environments, and research integrating various approaches of AI, thus has improved the accuracy of animal identification, with models consistently developing for better precision than before. AI can help not only with the real-time data but also in generative datasets [72], [81], [82]. It is, often, arguable that of using specific machine or deep learning techniques, rather than addressing just in umbrella term as AI. However, in most of given scenarios, AI techniques are most effective in terms of accuracy and model performance than traditional methods in visual ecological tasks associated with animal behaviors. Integrating AI techniques, not only enhances performance but also automate the process with less laborious efforts.

Fundings

The author mentioned that, no funding is received for this work.

Disclosure of Interests

The author declares no financial or personal competing interests.

References

[1] H. Wang et al., "Scientific discovery in the age of artificial intelligence," 2023. doi: 10.1038/s41586-023-06221-2.
[2] M. Krenn et al., "On scientific understanding with artificial intelligence," Nature Reviews Physics, vol. 4, no. 12, 2022, doi: 10.1038/s42254-022-00518-3.
[3] R. R. Malinda, "Biological data studies, scale-up the potential with machine learning," 2023. doi: 10.1038/s41431-023-01361-5.
[4] J. G. Greener, S. M. Kandathil, L. Moffat, and D. T. Jones, "A guide to machine learning for biologists," 2022. doi: 10.1038/s41580-021-00407-0.
[5] D. A. Boiko, R. MacKnight, B. Kline, and G. Gomes, "Autonomous chemical research with large language models," Nature, vol. 624, no. 7992, 2023, doi: 10.1038/s41586-023-06792-0.
[6] "Defining physicists' relationship with AI," 2022. doi: 10.1038/s42254-022-00544-1.
[7] P. Rajpurkar, E. Chen, O. Banerjee, and E. J. Topol, "AI in health and medicine," 2022. doi: 10.1038/s41591-021-01614-0.
[8] X. Tang, "The role of artificial intelligence in medical imaging research," BJR|Open, vol. 2, no. 1, 2020, doi: 10.1259/bjro.20190031.
[9] D. Paul, G. Sanap, S. Shenoy, D. Kalyane, K. Kalia, and R. K. Tekade, "Artificial intelligence in drug discovery and development," 2021. doi: 10.1016/j.drudis.2020.10.010.
[10] D. Tuia et al., "Perspectives in machine learning for wildlife conservation," 2022. doi: 10.1038/s41467-022-27980-y.
[11] D. Silvestro, S. Goria, T. Sterner, and A. Antonelli, "Improving biodiversity protection through artificial intelligence," Nat Sustain, vol. 5, no. 5, 2022, doi: 10.1038/s41893-022-00851-6.

[12] B. A. Han, K. R. Varshney, S. LaDeau, A. Subramaniam, K. C. Weathers, and J. Zwart, “A synergistic future for AI and ecology,” Proc Natl Acad Sci U S A, vol. 120, no. 38, 2023, doi: 10.1073/pnas.2220283120.
[13] M. Ryo, “Ecology with artificial intelligence and machine learning in Asia: A historical perspective and emerging trends,” Ecol Res, vol. 39, no. 1, 2024, doi: 10.1111/1440-1703.12425.
[14] K. Rafiq, S. Beery, M. S. Palmer, Z. Harchaoui, and B. Abrahms, “Generative AI as a tool to accelerate the field of ecology,” Nat Ecol Evol, vol. 9, no. 3, pp. 378–385, Jan. 2025, doi: 10.1038/s41559-024-02623-1.
[15] S. A. Reynolds et al., “The potential for AI to revolutionize conservation: a horizon scan,” Trends Ecol Evol, vol. 40, no. 2, pp. 191–207, Feb. 2025, doi: 10.1016/j.tree.2024.11.013.
[16] O. Elemento, C. Leslie, J. Lundin, and G. Tourassi, “Artificial intelligence in cancer research, diagnosis and therapy,” 2021. doi: 10.1038/s41568-021-00399-1.
[17] S. J. Shettleworth, “Animal cognition and animal behaviour,” 2001. doi: 10.1006/anbe.2000.1606.
[18] F. (editor) Huntingford, The study of animal behaviour. Springer Science & Business Media, 2012.
[19] A. Manning and Marian Stamp Dawkins, An introduction to animal behaviour. Cambridge University Press, 2012.
[20] J. Kendall-Bar et al., “Challenges and solutions for ecologists adopting AI,” Jan. 29, 2025. doi: 10.32942/X2FK8J.
[21] I. D. Couzin and C. Heins, “Emerging technologies for behavioral research in changing environments,” 2023. doi: 10.1016/j.tree.2022.11.008.
[22] N. Kleanthous, A. J. Hussain, W. Khan, J. Sneddon, A. Al-Shamma’a, and P. Liatsis, “A survey of machine learning approaches in animal behaviour,” Neurocomputing, vol. 491, 2022, doi: 10.1016/j.neucom.2021.10.126.
[23] R. Otsuka et al., “Exploring deep learning techniques for wild animal behaviour classification using animal-borne accelerometers,” Methods Ecol Evol, vol. 15, no. 4, 2024, doi: 10.1111/2041-210X.14294.
[24] G. Wang, “Machine learning for inferring animal behavior from location and movement data,” Ecol Inform, vol. 49, 2019, doi: 10.1016/j.ecoinf.2018.12.002.
[25] J. J. Valletta, C. Torney, M. Kings, A. Thornton, and J. Madden, “Applications of machine learning in animal behaviour studies,” 2017. doi: 10.1016/j.anbehav.2016.12.005.

[26] T. Maekawa et al., “Deep learning-assisted comparative analysis of animal trajectories with DeepHL,” Nat Commun, vol. 11, no. 1, 2020, doi: 10.1038/s41467-020-19105-0.
[27] A. Zamansky, A. Sinitca, D. Van Der Linden, and D. Kaplun, “Automatic Animal Behavior Analysis: Opportunities for Combining Knowledge Representation with Machine Learning,” in Procedia Computer Science, 2021. doi: 10.1016/j.procs.2021.04.187.
[28] E. Fazzari, D. Romano, F. Falchi, and C. Stefanini, “Animal Behavior Analysis Methods Using Deep Learning: A Survey,” May 2024.
[29] J. V. Congdon, M. Hosseini, E. F. Gading, M. Masousi, M. Franke, and S. E. Macdonald, “The Future of Artificial Intelligence in Monitoring Animal Identification, Health, and Behaviour,” Animals, vol. 12, no. 13, 2022, doi: 10.3390/ani12131711.
[30] N. Wilson, “Artificial intelligence helps drive new frontiers in ecology,” Bioscience, vol. 74, no. 5, pp. 306–311, Jun. 2024, doi: 10.1093/biosci/biae016.
[31] A. Bin Rashid and M. A. K. Kausik, “AI revolutionizing industries worldwide: A comprehensive overview of its diverse applications,” Hybrid Advances, vol. 7, p. 100277, Dec. 2024, doi: 10.1016/j.hybadv.2024.100277.
[32] M. D. Lürig, S. Donoughe, E. I. Svensson, A. Porto, and M. Tsuboi, “Computer Vision, Machine Learning, and the Promise of Phenomics in Ecology and Evolutionary Biology,” 2021. doi: 10.3389/fevo.2021.642774.
[33] J. Wang et al., “Deep High-Resolution Representation Learning for Visual Recognition,” IEEE Trans Pattern Anal Mach Intell, vol. 43, no. 10, 2021, doi: 10.1109/TPAMI.2020.2983686.
[34] C. Angermueller, T. Pärnamaa, L. Parts, and O. Stegle, “Deep learning for computational biology,” Mol Syst Biol, vol. 12, no. 7, 2016, doi: 10.15252/msb.20156651.
[35] J. J. Bolhuis, L. A. Giraldeau, and J. A. Hogan, “the study of animal behavior,” in The Behavior of Animals: Mechanisms, Function, and Evolution: Second Edition, 2021. doi: 10.1002/9781119109556.ch1.
[36] B. Koger, A. Deshpande, J. T. Kerby, J. M. Graving, B. R. Costelloe, and I. D. Couzin, “Quantifying the movement, behaviour and environmental context of group-living animals using drones and computer vision,” Journal of Animal Ecology, vol. 92, no. 7, 2023, doi: 10.1111/1365-2656.13904.
[37] M. Patel, Y. Gu, L. C. Carstensen, M. E. Hasselmo, and M. Betke, “Animal Pose Tracking: 3D Multimodal Dataset and

Token-based Pose Optimization," Int J Comput Vis, vol. 131, no. 2, 2023, doi: 10.1007/s11263-022-01714-5.
[38] S. Broomé et al., "Going Deeper than Tracking: A Survey of Computer-Vision Based Recognition of Animal Pain and Emotions," Int J Comput Vis, vol. 131, no. 2, 2023, doi: 10.1007/s11263-022-01716-3.
[39] S. Quaade, A. Vallebueno, O. D. N. Alcabes, K. T. Rodolfa, and D. E. Ho, "Remote sensing and computer vision for marine aquaculture," Sci Adv, vol. 10, no. 42, Oct. 2024, doi: 10.1126/sciadv.adn4944.
[40] B. Zion, "The use of computer vision technologies in aquaculture - A review," 2012. doi: 10.1016/j.compag.2012.07.010.
[41] K. F. A. Darras et al., "Eyes on nature: Embedded vision cameras for terrestrial biodiversity monitoring," Methods Ecol Evol, vol. 15, no. 12, pp. 2262–2275, Dec. 2024, doi: 10.1111/2041-210X.14436.
[42] J. D. Blair, K. M. Gaynor, M. S. Palmer, and K. E. Marshall, "A gentle introduction to computer vision-based specimen classification in ecological datasets," Journal of Animal Ecology, vol. 93, no. 2, 2024, doi: 10.1111/1365-2656.14042.
[43] A. Saleh, M. Sheaves, and M. Rahimi Azghadi, "Computer vision and deep learning for fish classification in underwater habitats: A survey," Fish and Fisheries, vol. 23, no. 4, 2022, doi: 10.1111/faf.12666.
[44] B. G. Weinstein, "A computer vision for animal ecology," 2018. doi: 10.1111/1365-2656.12780.
[45] A. M. Vukicevic, M. Petrovic, P. Milosevic, A. Peulic, K. Jovanovic, and A. Novakovic, "A systematic review of computer vision-based personal protective equipment compliance in industry practice: advancements, challenges and future directions," Artif Intell Rev, vol. 57, no. 12, p. 319, Oct. 2024, doi: 10.1007/s10462-024-10978-x.
[46] S. Zhu et al., "Intelligent Computing: The Latest Advances, Challenges, and Future," Intelligent Computing, vol. 2, 2023, doi: 10.34133/icomputing.0006.
[47] Z. Chen et al., "AlphaTracker: a multi-animal tracking and behavioral analysis tool," Front Behav Neurosci, vol. 17, 2023, doi: 10.3389/fnbeh.2023.1111908.
[48] M. Perez and C. Toler-Franklin, "CNN-Based Action Recognition and Pose Estimation for Classifying Animal Behavior from Videos: A Survey," Jan. 2023.
[49] T. D. Pereira et al., "SLEAP: A deep learning system for multi-animal pose tracking," Nat Methods, vol. 19, no. 4, 2022, doi: 10.1038/s41592-022-01426-1.

[50] J. Lauer et al., “Multi-animal pose estimation, identification and tracking with DeepLabCut,” Nat Methods, vol. 19, no. 4, 2022, doi: 10.1038/s41592-022-01443-0.
[51] D. Biderman et al., “Lightning Pose: improved animal pose estimation via semi-supervised learning, Bayesian ensembling and cloud-native open-source tools,” Nat Methods, vol. 21, no. 7, 2024, doi: 10.1038/s41592-024-02319-1.
[52] T. W. Dunn et al., “Geometric deep learning enables 3D kinematic profiling across species and environments,” Nat Methods, vol. 18, no. 5, 2021, doi: 10.1038/s41592-021-01106-6.
[53] P. Karashchuk, J. C. Tuthill, and B. W. Brunton, “The DANNCE of the rats: a new toolkit for 3D tracking of animal behavior,” Nat Methods, vol. 18, no. 5, 2021, doi: 10.1038/s41592-021-01110-w.
[54] V. Panadeiro, A. Rodriguez, J. Henry, D. Wlodkowic, and M. Andersson, “A review of 28 free animal-tracking software applications: current features and limitations,” 2021. doi: 10.1038/s41684-021-00811-1.
[55] F. Schindler and V. Steinhage, “Instance segmentation and tracking of animals in wildlife videos: SWIFT - segmentation with filtering of tracklets,” Ecol Inform, vol. 71, 2022, doi: 10.1016/j.ecoinf.2022.101794.
[56] F. Schindler, V. Steinhage, S. T. S. van Beeck Calkoen, and M. Heurich, “Action Detection for Wildlife Monitoring with Camera Traps Based on Segmentation with Filtering of Tracklets (SWIFT) and Mask-Guided Action Recognition (MAROON),” Applied Sciences (Switzerland), vol. 14, no. 2, 2024, doi: 10.3390/app14020514.
[57] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, “Densely connected convolutional networks,” in Proceedings - 30th IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017, 2017. doi: 10.1109/CVPR.2017.243.
[58] S. Kiranyaz, O. Avci, O. Abdeljaber, T. Ince, M. Gabbouj, and D. J. Inman, “1D convolutional neural networks and applications: A survey,” Mech Syst Signal Process, vol. 151, 2021, doi: 10.1016/j.ymssp.2020.107398.
[59] A. S. Abangan, D. Kopp, and R. Faillettaz, “Artificial intelligence for fish behavior recognition may unlock fishing gear selectivity,” 2023. doi: 10.3389/fmars.2023.1010761.
[60] A. Saleh, M. Sheaves, D. Jerry, and M. Rahimi Azghadi, “Applications of deep learning in fish habitat monitoring: A tutorial and survey,” 2024. doi: 10.1016/j.eswa.2023.121841.

[61] R. Arablouei, L. Wang, L. Currie, J. Yates, F. A. P. Alvarenga, and G. J. Bishop-Hurley, “Animal behavior classification via deep learning on embedded systems,” Comput Electron Agric, vol. 207, 2023, doi: 10.1016/j.compag.2023.107707.

[62] J. Kwon et al., “SUBTLE: An Unsupervised Platform with Temporal Link Embedding that Maps Animal Behavior,” Int J Comput Vis, vol. 132, no. 10, pp. 4589–4615, Oct. 2024, doi: 10.1007/s11263-024-02072-0.

[63] M. Fuchs, E. Genty, K. Zuberbühler, and P. Cotofrei, “ASBAR: an Animal Skeleton-Based Action Recognition framework. Recognizing great ape behaviors in the wild using pose estimation with domain adaptation,” Aug. 02, 2024. doi: 10.7554/eLife.97962.1.

[64] E. Zaidan and I. A. Ibrahim, “AI Governance in a Complex and Rapidly Changing Regulatory Landscape: A Global Perspective,” Humanit Soc Sci Commun, vol. 11, no. 1, p. 1121, Sep. 2024, doi: 10.1057/s41599-024-03560-x.

[65] A. Bin Rashid and M. A. K. Kausik, “AI revolutionizing industries worldwide: A comprehensive overview of its diverse applications,” Hybrid Advances, vol. 7, p. 100277, Dec. 2024, doi: 10.1016/j.hybadv.2024.100277.

[66] M. Q. R. Pembury Smith and G. D. Ruxton, “Camouflage in predators,” Biological Reviews, vol. 95, no. 5, 2020, doi: 10.1111/brv.12612.

[67] J. V. De Alcantara Viana, C. Vieira, R. C. Duarte, and G. Q. Romero, “Predator responses to prey camouflage strategies: A meta-analysis,” Proceedings of the Royal Society B: Biological Sciences, vol. 289, no. 1982, 2022, doi: 10.1098/rspb.2022.0980.

[68] M. C. Stoddard and D. Osorio, “Animal coloration patterns: Linking spatial vision to quantitative analysis,” American Naturalist, vol. 193, no. 2, 2019, doi: 10.1086/701300.

[69] J. P. Renoult, A. Kelber, and H. M. Schaefer, “Colour spaces in ecology and evolutionary biology,” Biological Reviews, vol. 92, no. 1, 2017, doi: 10.1111/brv.12230.

[70] I. C. Cuthill et al., “The biology of color,” 2017. doi: 10.1126/science.aan0221.

[71] J. G. Fennell, L. Talas, R. J. Baddeley, I. C. Cuthill, and N. E. Scott-Samuel, “The Camouflage Machine: Optimizing protective coloration using deep learning with genetic algorithms,” Evolution (N Y), vol. 75, no. 3, 2021, doi: 10.1111/evo.14162.

[72] F. Xiao et al., “A Survey of Camouflaged Object Detection and Beyond,” CAAI Artificial Intelligence Research, p. 9150044, Dec. 2024, doi: 10.26599/AIR.2024.9150044.

[73] G. H. JACOBS, "THE DISTRIBUTION AND NATURE OF COLOUR VISION AMONG THE MAMMALS," Biological Reviews, vol. 68, no. 3, 1993, doi: 10.1111/j.1469-185x.1993.tb00738.x.
[74] C. S. Ike, N. Muhammad, N. Bibi, S. Alhazmi, and F. Eoghan, "Discriminative context-aware network for camouflaged object detection," Front Artif Intell, vol. 7, Mar. 2024, doi: 10.3389/frai.2024.1347898.
[75] Y. Wen, W. Ke, and H. Sheng, "Camouflaged Object Detection Based on Deep Learning with Attention-Guided Edge Detection and Multi-Scale Context Fusion," Applied Sciences (Switzerland), vol. 14, no. 6, 2024, doi: 10.3390/app14062494.
[76] C. Guo and H. Huang, "Enhancing camouflaged object detection through contrastive learning and data augmentation techniques," Eng Appl Artif Intell, vol. 141, p. 109703, Feb. 2025, doi: 10.1016/j.engappai.2024.109703.
[77] B. Ge, X. Peng, C. Xia, and H. Chen, "Camouflaged object detection with integrated feature fusion and boundary optimization," Multimed Syst, vol. 31, no. 4, p. 284, Aug. 2025, doi: 10.1007/s00530-025-01879-2.
[78] F. Xiao et al., "A Survey of Camouflaged Object Detection and Beyond," Aug. 2024.
[79] R. Kamble and P. Rajarajeswari, "Revealing Hidden Patterns: A Deep Learning Approach to Camouflage Detection," International Journal of Computational Methods and Experimental Measurements, vol. 12, no. 1, pp. 97–105, Mar. 2024, doi: 10.18280/ijcmem.120111.
[80] C. Shi, L. Zhao, R. Wang, K. Zhang, F. Kong, and C. Duan, "Multi-information guided camouflaged object detection," Image Vis Comput, vol. 156, p. 105470, Apr. 2025, doi: 10.1016/j.imavis.2025.105470.
[81] C. Zhang, H. Bi, T. Z. Xiang, R. Wu, J. Tong, and X. Wang, "Collaborative Camouflaged Object Detection: A Large-Scale Dataset and Benchmark," IEEE Trans Neural Netw Learn Syst, 2023, doi: 10.1109/TNNLS.2023.3317091.
[82] H. Bi, C. Zhang, K. Wang, J. Tong, and F. Zheng, "Rethinking Camouflaged Object Detection: Models and Datasets," IEEE Transactions on Circuits and Systems for Video Technology, vol. 32, no. 9, 2022, doi: 10.1109/TCSVT.2021.3124952.
[83] V. Papaspyros, R. Escobedo, A. Alahi, G. Theraulaz, C. Sire, and F. Mondada, "Predicting the long-term collective behaviour of fish pairs with deep learning," J R Soc Interface, vol. 21, no. 212, 2024, doi: 10.1098/rsif.2023.0630.