# Integration of Deep Learning and Knowledge Representation in the Automated Analysis of Animal Behavior

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***Abstract-*** The behavior of animals is a good way to see how well a living being has adapted to its surroundings and how well it is doing overall. Researchers and viewers can learn a great deal about social dynamics, health, ecological relationships, and neuroethological aspects of animals' lives by closely observing their behaviors and interactions. Even while cutting-edge deep learning models have shown impressive accuracy in categorizing different types of animal data, there is still a lack of use for them in animal behavior research. The goal of the developing area of computational animal behavior analysis is to use Deep Learning methods to assist with animal behavior analysis. It is commonly accepted in a number of scientific fields pertaining to animals that computational methods that enable the measurement of animal behavior are necessary. Modern and innovative Computer vision methods are used with machine learning (ML) techniques in computational animal behavior analysis methodologies. Deep learning techniques and architectures used in audiovisual, visual, and auditory approaches for behavioral recognition. Furthermore, the paper provides a thorough analysis of the fundamental issues facing this field of study by reviewing existing datasets on behavior of animals.

***Keywords-*** Deep Learning, Computer Vision, Artificial intelligence, Machine learning, animal behavior and data processing.

## I. INTRODUCTION

Animal behavior is the range of behaviors, responses, and patterns of activity that animals exhibit in response to their surroundings, other living things, and internal signals [1]. This broad field encompasses a wide spectrum of behaviors, from learnt conduct and complex social interactions to basic reflexes and natural instincts. The observation, explanation, and Numerous obstacles that affect animal behavior research have a profound impact on the usefulness and effectiveness of its applications. These difficulties are present in the methods used to collect data, the complexities of data analysis (both in terms of location and processing requirements), and the intricate process of data annotation.

understanding of how animals interact with one another and their environment are all part of the study of animal behavior. The field of animal behavior research is now changing significantly because of the development of advanced behavior detection technologies and the ongoing introduction of novel experimental techniques.

An essential technique for studying animal behavior is deep learning. Computers can now automatically identify patterns and features from large datasets due to this innovative area of artificial intelligence. Additionally, deep learning is essential to the creation of complex behavior detection systems. Because of these systems' ability to automatically identify and categories a variety of behaviors, researchers may shift their attention from tedious manual data annotation to result interpretation [2].

The scalability and effectiveness of animal behavior studies are improved by this speedup in data processing and behavior recognition, which ushers in a new era of learning and comprehension in this continuously developing area. We present a comprehensive overview of the current methods and technologies used in animal behavior analysis. This involves a thorough examination of the methods and strategies that are currently widely used in this field.

## II. MOTIVATION

In this section, we elaborate on the fundamental reasons that support the deep learning study of animal behavior, outlining the various benefits and goals that come with this specialized field of study. While acknowledging the complex issues brought about by differences in study setups, we also carefully examine the main constraints that define this subject.

***Limitations in Investigation of Animal Behavior***

Entering the mobile device market adds another level of complexity to the difficulties faced by deep learning applications. Storage constraints remain a problem when models are implemented on these devices [3]. Techniques like Quantized-CNN try to solve the problem of striking a balance between reliable object detection and effective data compression. The constant challenge, though, is to strike this balance without sacrificing accuracy, which is essential for the dependability of behavioral analysis.

In the field of labeling and annotation, tagging big datasets for every animal is hampered by practical and financial limitations [4]. Because deep learning models mostly depend on labelled datasets for efficient training, this bottleneck hinders their scalability. The credibility of further studies is impacted by the impracticality of manual labeling, which raises serious questions regarding the quality and scope of behavioral datasets. Furthermore, these difficulties also apply to novel techniques that have the potential to offer deeper understandings of animal behavior, like multi-view recordings [5]. However, the lack of correlation between data sources makes it difficult to correlate social behaviors from various viewpoints. To extract valuable insights, robust algorithms that can handle a variety of animal sizes, shifting appearances, clutter, occlusions, and unpredictable surroundings are essential. These difficulties highlight how urgently technology innovation that meets the requirements of both controlled and natural environments is needed.

***Objective of Investigation Animal Behavior***

Animal behavior research has several benefits, enhancing our understanding of the natural world and offering useful applications in a variety of fields, such as robotics, neurology, pharmacology, medicine, agriculture, and ecology. There are five main benefits to researching animal behavior:

- The conservation of biodiversity depends on our ability to comprehend animal behavior [6]. Effective conservation efforts and the protection of endangered species depend on an understanding of behaviors like eating habits, reproductive techniques, and migration patterns.
- Understanding the ecological processes of ecosystems is possible through the behavior of animals [7]. Through behavioral investigations, scientists can better understand how animals interact with their surroundings, including how they contribute to seed dispersal, nutrient cycling, and predator-prey relationships.
- The study of animal behavior may have consequences for human health and medicine. Research on animal models, for instance, aids in the study of specific illnesses and the creation of possible cures. Our knowledge of the psychology and neuroscience underlying human behavior is also enhanced by behavioral research on animals [8].
- Understanding the behavior of pest species can help design successful pest control tactics in agriculture, even though at the moment it is largely restricted to pest identification [9]. Farmers can control crop damage and lessen their reliance on dangerous pesticides by using this knowledge.
- The principles guiding social structures and interactions can be understood by studying the social behaviors of animals. This information can help us understand social dynamics in general and be applied in disciplines like psychology and sociology [10].

Annotated data is necessary for deep learning to be effective, particularly for supervised methods. Labeling can be iterative in tasks like posture estimation and classification, but manual annotation is still inevitable. A small section of the dataset must be annotated, a network must be trained, predictions must be made on fresh images, labels must be corrected, and the process must be repeated several times.

## III. LITERATURE SURVEY

The methods used for data collecting and synthesis are described in this section. Data was first gathered by means of methodical searches on scholarly sources such as the Springer Database, IEEE Xplore, and Google Scholar. The apparent dearth of literature in these areas in comparison to research involving farm animals and neuroethological, which are often centered on mice, prompted the idea to utilize different questions for insects and wild animals. Therefore, it was essential to formulate particular questions that would cover a wider range of animal species.

***Pose Estimation-Based Methods***

A basic method frequently employed in the analysis of animal behaviors in conjunction with object identification is pose estimation, which is the act of recognizing and determining the position and orientation of objects. Beginning with Human Pose Estimation (HPE), Mathis et al. led the transition to Animal Pose Estimation (APE) with DeepLabCut [11] and Pereira et al. with LEAP [12], which in turn led to SLEAP [13].

Convolution layers are used in the single-animal pose estimation model LEAP, which produces confidence maps that show the probability distribution for each unique body key point. This architectural layout, which has three sets of convolutional layers and is simple, is shown in Figure 1. To reduce computational complexity, max pooling is used to terminate the first two sets. A confidence map is then produced for each image by applying transposed convolution, which restores the original dimensions of the images while adding a depth equal to the number of key points. T-LEAP was introduced because, despite its simplicity, the LEAP model has problems in non-laboratory environments because of things like occlusion [14]. Although T-LEAP uses 3D convolution rather than 2D convolution, it maintains the LEAP architecture. Four consecutive frames taken from movies make up the input of T-LEAP, which increases the model's resilience. Notably, T-LEAP continues to priorities posture estimate for a single animal.

Later, the creator of LEAP unveiled Social LEAP (SLEAP), an improved version that combines top-down and bottom-up techniques to effectively handle the difficulties involved in multi-animal pose assessment. In the top-down approach, SLEAP initially recognises people before locating the appropriate body part. In contrast to LEAP, SLEAP integrates this method without requiring an extra object detection framework.

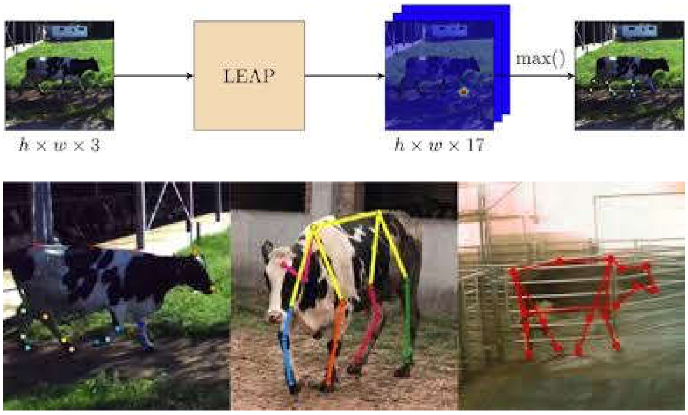


Figure 1: shows the architecture of LEAP and T-LEAP

The DeepLabCut (DLC) has changed a lot over time. Originally intended as a single-animal posture estimation technique, it creates confidence maps for keypoints by combining a pretrained ResNet-50 backbone with additional deconvolutional layers over it. Using Imagenet pretrained weights, this method enabled DLC to efficiently predict skeletons with little data. It is crucial to recognize recent developments in animal pose estimation architectures, even though DLC and SLEAP are still the most often used pose estimate techniques in behavior analysis for animal behavior classification. There have been several noteworthy approaches introduced:

- SemiMultiPose[15], which builds on DeepGraphPose[16] and DirectPose[17], presents a semi-supervised multi-animal posture prediction method. The technique uses a ResNet backbone to process both labelled and unlabelled frames as input. This result in a compact representation that is fed into three branches: one for keypoint detection (B1), one for bounding box heatmaps (B2), and a third for keypoint detection (B3). SemiMultiPose contributes to B1 by attempting to produce pseudo keypoint coordinates for the self-supervised branch from B2 and B3. In comparison to SLEAP, the network has demonstrated increased accuracy.
- There are two ways that Lightning Pose [18] takes advantage of the spatiotemporal statistics of unlabelled films. The network is penalised for predictions that deviate from a low-dimensional subspace of realistic body configurations, multiple-view geometry, or the smoothness of physical motion when unsupervised training objectives are first introduced. Second, a novel network design that uses temporal context from nearby unlabelled frames to predict poses for a given frame is proposed.
- A unique approach was presented by Bhattacharya et al. [19] for identifying various animals' poses from unlabelled data. The method entails applying an edge detection algorithm to the animal's body after removing background information from each image. The mobility of the edge pixels is then monitored, and body components are segmented using agglomerative clustering.

The next stage is to process the data to identify certain behaviors after acquiring the skeletal representation of every animal in every frame, whether from photos or movies. Statistical techniques provide an efficient way to analyze the trajectories obtained from pose estimation. Classifying postures and linking them to certain behaviors requires the use of machine learning for the analysis of pose estimation trajectories. One of the most straightforward methods is to employ a Nearest-Neighbor classifier. Other authors used convolutional and recurrent neural networks, with straightforward methods such processing trajectories for behavioral conclusions utilizing 1D convolutional neural networks and Long Short-Term Memory (LSTM). In order to increase the feature space, some authors streamlined the classification process by incorporating a non-linear clustering phase. Multilayer Perceptron (MLP) was then used for classification, showing benefits in classification. An emerging trend in animal behavior analysis is the application of unsupervised learning techniques. A novel approach to processing trajectories obtained by DeepLabCut using a Variation Auto-Encoder (VAE). They next use a Hidden Markov Model (HMM) to identify underlying patterns in the newly represented trajectories. Trajectories are useful for detecting anomalies as well as for identifying particular behaviors.

Object identification is one of the most popular deep learning approaches for examining animal behavior when combined with posture estimation techniques. Because of its proven value in animal recognition and detection [20], it is widely used, which has led researchers to shift their attention to the study of animal welfare and behavior. One of the most popular designs for identifying animal behavior is Faster R-CNN [22] and YOLO [21] in particular. Object detection has two functions: it may quantify and track particular behaviors in addition to detecting behavior instantly using picture or video frame analysis. Researchers can measure the length of time and frequency of discrete activities by precise single-frame analysis, counting, and frame-by-frame inspection. Both the measurement and tracking of certain behaviors as well as the instantaneous behavior detection via image or video frame analysis are functions of object detection. Through precise single-frame analysis, counting, and frame-by-frame inspection, researchers may measure the frequency and duration of discrete events. One study of the animal and a direct classification of its behavior from a single photograph can achieve effective instant detection. In this regard, deep learning object detection models are useful for directly detecting behaviors such positional activities (e.g., mating, standing, feeding, spreading, fighting, and drinking) for the thorough examination of stress behaviors and animal health.

## IV. ABOUT DATASET

The standardization of skeletal features when used across several animal species is a noteworthy finding in the context of datasets designed for pose estimation. By removing the requirement for species-specific networks, this standardization makes it easier to train a single network. On the other hand, datasets that are unique

to a single animal species show complex skeletal patterns that are adapted to the subtleties of that species' anatomy. For example, it might be possible to discern the proximal and distal ends of crickets' antennae with accuracy, but this level of detail might not apply to other insect species like horses.
For determining static positions, such as whether an animal is standing or lying down, still photos are enough. But the key to identifying dynamic actions and behaviors is to record and analyze videos—or more accurately, brief video snippets. Because these recordings are purposefully short, they only highlight the pertinent action event, guaranteeing precise classification through the use of deep learning algorithms.

The main goals of many databases, which include identification, detection, pose estimate, and tracking, must be taken into account. Although not specifically created for behavioral analysis, it is important to recognize that a number of datasets have been useful in this field despite this approach.

## V. PROPOSED FRAMEWORK

A variety of data kinds can be subjected to automatic analysis. One source of animal behavioral data is bio-logging tags or wearable technology affixed to the animal which gathers information on the animal's surroundings, movements, behaviors, and physiological traits.

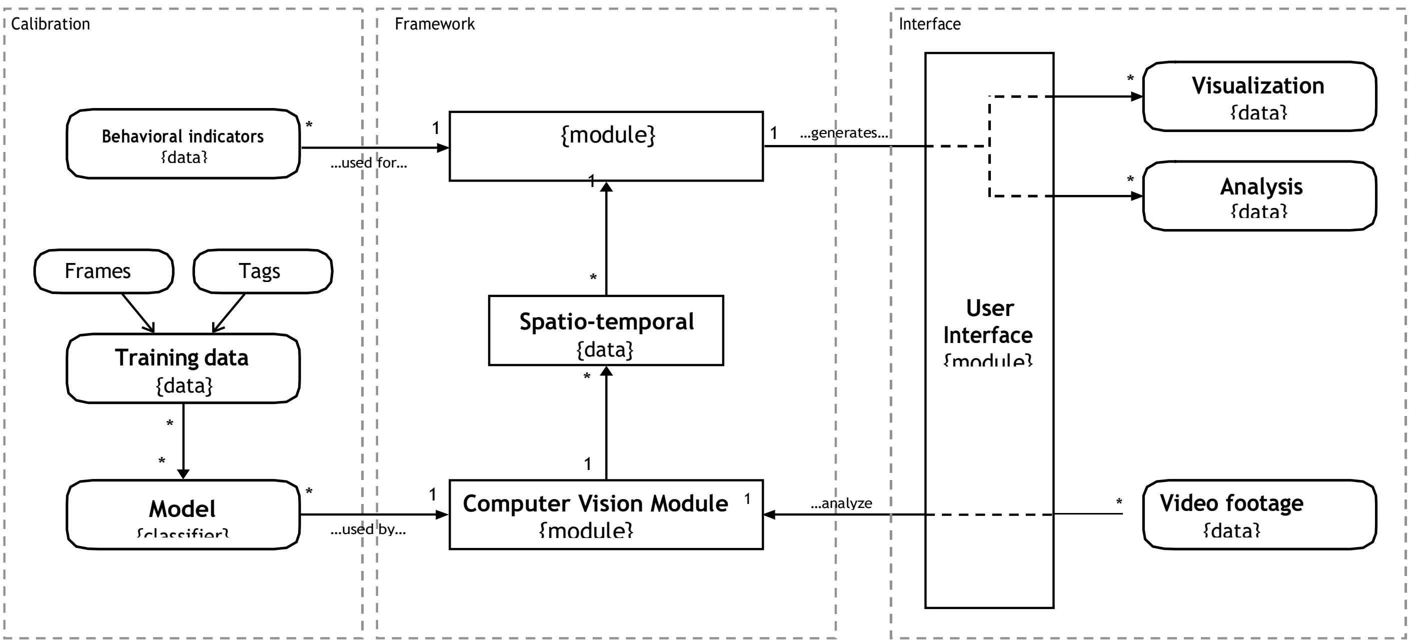


Figure 2: Proposed Computational Animal Behavior Framework

Video footage is another common form of data that we will be focusing on from now on because of its widespread use in animal science. Proposed framework used for analyzing movement parameters of animal in video footage. This is based on deep learning neural networks. Analysis is its present emphasis, and the models that underpin it have already been trained on a number of datasets gathered from veterinary clinics and canine behavioral testing experiments

The architecture of the Proposed Computational Animal Behavior Framework is shown in Figure 2. It is composed of two levels: (i) computer vision layers that use neural network-based models for posture classification and dog detection, and (ii) the analysis module that gathers and measures the desired parameters from the spatiotemporal data. Using a domain-specific logical specification language,

Figure 3: Studying facial preference data collected in experimental setup.

## VI. Discussion and Future Research

We have highlighted in this work the exciting prospects for the Knowledge Representation community to participate in the new and developing field of computational animal behavior analysis based on Deep learning. We have shown a tangible example of describing the parameters of interest in the proposed system using a specification language. Concerning the impressibility of such domain-specific languages pertaining to spatiotemporal notions enhanced with species-specific features (e.g., distinct body parts) and contextual information about the animal's environment, this raises intriguing research problems and challenges. Furthermore, our goal is to make these languages machine-interpretable so that the system can be configured automatically, which presents another research problem.

## References

[1]. André EX Brown and Benjamin de Bivort. 2017. The study of animal behavior as a physical science. bioRxiv (2017).
[2]. Reza Arablouei, Liang Wang, Lachlan Currie, Jodan Yates, Flavio AP Alvarenga, and Greg J Bishop-Hurley. 2023. Animal behavior classification via deep learning on embedded systems. Computers and Electronics in Agriculture 207 (2023), 107707.
[3]. Shuo Cao, Dean Zhao, Xiaoyang Liu, and Yueping Sun. 2020. Real-time robust detector for underwater live crabs based on deep learning. Computers and Electronics in Agriculture 172 (2020), 105339.
[4]. Samayan Bhattacharya and Sk Shahnawaz. 2021. Pose recognition in the wild: Animal pose estimation using agglomerative clustering and contrastive learning. arXiv preprint arXiv:2111.08259 (2021).
[5]. Zheheng Jiang, Feixiang Zhou, Aite Zhao, Xin Li, Ling Li, Dacheng Tao, Xuelong Li, and Huiyu Zhou. 2021. Multi-view mouse social behavior recognition with deep graphic model. IEEE Transactions on Image Processing 30 (2021), 5490–5504.
[6]. Ellen M Ditria, Sebastian Lopez-Marcano, Michael Sievers, Eric L Jinks, Christopher J Brown, and Rod M Connolly. 2020. Automating the analysis of fish abundance using object detection: optimizing animal ecology with deep learning. Frontiers in Marine Science (2020), 429.
[7]. Hüseyin Gökhan Akçay, Bekir Kabasakal, Duygugül Aksu, Nusret Demir, Melih Öz, and Ali Erdogan. 2020. Automated bird counting with deep learning for regional bird distribution mapping. Animals 10, 7 (2020), 1207.
[8]. Genaro A Coria-Avila, James G Pfaus, Agustín Orihuela, Adriana Domínguez-Oliva, Nancy José-Pérez, Laura Astrid Hernández, and Daniel Mota-Rojas. 2022. The neurobiology of behavior and its applicability for animal welfare: A review. Animals 12, 7 (2022), 928.
[9]. Reza Arablouei, Ziwei Wang, Greg J Bishop-Hurley, and Jiajun Liu. 2023. Multimodal sensor data fusion for in-situ classification of animal behavior using accelerometry and GNSS data. Smart Agricultural Technology 4 (2023), 100163.
[10]. Ali Alameer, Stephanie Buijs, Niamh O'Connell, Luke Dalton, Mona Larsen, Lene Pedersen, and Ilias Kyriazakis. 2022. Automated detection and quantification of contact behaviour in pigs using deep learning. biosystems engineering 224 (2022), 118–130.
[11]. Alexander Mathis, Pranav Mamidanna, Kevin M Cury, Taiga Abe, Venkatesh N Murthy, Mackenzie Weygandt Mathis, and Matthias Bethge. 2018. DeepLabCut: markerless pose estimation of user-defined body parts with deep learning. Nature neuroscience 21, 9 (2018), 1281–1289.
[12]. Talmo D Pereira, Diego E Aldarondo, Lindsay Willmore, Mikhail Kislin, Samuel S-H Wang, Mala Murthy, and Joshua W Shaevitz. 2019. Fast animal pose estimation using deep neural networks. Nature methods 16, 1 (2019), 117–125.
[13] Talmo D Pereira, Nathaniel Tabris, Arie Matsliah, David M Turner, Junyu Li, Shruthi Ravindranath, Eleni S Papadoyannis, Edna Normand, David S Deutsch, Z Yan Wang, et al. 2022. SLEAP: A deep learning system for multi-animal pose tracking. Nature methods 19, 4 (2022), 486–495.
[14]. Helena Russello, Rik van der Tol, and Gert Kootstra. 2022. T-LEAP: Occlusion-robust pose estimation of walking cows using temporal information. Computers and Electronics in Agriculture 192 (2022), 106559.
[15]. Ari Blau, Christoph Gebhardt, Andres Bendesky, Liam Paninski, and Anqi Wu. 2022. SemiMultiPose: A Semi-supervised Multi-animal Pose Estimation Framework. arXiv preprint arXiv:2204.07072 (2022).
[16]. Anqi Wu, Estefany Kelly Buchanan, Matthew Whiteway, Michael Schartner, Guido Meijer, Jean-Paul Noel, Erica Rodriguez, Claire Everett, Amy Norovich, Evan Schaffer, et al. 2020. Deep Graph Pose: a semi-supervised deep graphical model for improved animal pose tracking. Advances in Neural Information Processing Systems 33 (2020), 6040–6052.
[17]. Zhi Tian, Hao Chen, and Chunhua Shen. 2019. Directpose: Direct end-to-end multi-person pose estimation. arXiv preprint arXiv:1911.07451 (2019).
[18]. Dan Biderman, Matthew R Whiteway, Cole Hurwitz, Nicholas Greenspan, Robert S Lee, Ankit Vishnubhotla, Richard Warren, Federico Pedraja, Dillon Noone, Michael Schartner, et al. 2023. Lightning Pose: improved animal pose estimation via semi-supervised learning, Bayesian ensembling, and cloud-native open-source tools. bioRxiv (2023).
[19]. Samayan Bhattacharya and Sk Shahnawaz. 2021. Pose recognition in the wild: Animal pose estimation using agglomerative clustering and contrastive learning. arXiv preprint arXiv:2111.08259 (2021).
[20]. Shoubhik Chandan Banerjee, Khursheed Ahmad Khan, and Rati Sharma. 2023. Deep-worm-tracker: Deep learning methods for accurate detection and tracking for behavioral studies in C. elegans. Applied Animal Behaviour Science 266 (2023), 106024.

[21] Joseph Redmon, Santosh Divvala, Ross Girshick, and Ali Farhadi. 2016. You only look once: Unified, real-time object detection. In Proceedings of the IEEE conference on computer vision and pattern recognition. 779–788.
[22] Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun. 2015. Faster r-cnn: Towards real-time object detection with region proposal networks. Advances in neural information processing systems 28 (2015)

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