

# From beasts to bytes: Revolutionizing zoological research with artificial intelligence

Yu-Juan Zhang<sup>1</sup>, Zeyu Luo<sup>1</sup>, Yawen Sun<sup>1</sup>, Junhao Liu<sup>1</sup>, Zongqing Chen<sup>2,3,\*</sup>

<sup>1</sup> *Chongqing Key Laboratory of Vector Insects; Chongqing Key Laboratory of Animal Biology; College of Life Science, Chongqing Normal University, Chongqing 401331, China*

<sup>2</sup> *School of Mathematical Sciences, Chongqing Normal University, Chongqing 401331, China*

<sup>3</sup> *Chongqing National Center for Applied Mathematics, Chongqing Normal University, Chongqing 401331, China*

## ABSTRACT

Since the late 2010s, Artificial Intelligence (AI) including machine learning, boosted through deep learning, has boomed as a vital tool to leverage computer vision, natural language processing and speech recognition in revolutionizing zoological research. This review provides an overview of the primary tasks, core models, datasets, and applications of AI in zoological research, including animal classification, resource conservation, behavior, development, genetics and evolution, breeding and health, disease models, and paleontology. Additionally, we explore the challenges and future directions of integrating AI into this field. Based on numerous case studies, this review outlines various avenues for incorporating AI into zoological research and underscores its potential to enhance our understanding of the intricate relationships that exist within the animal kingdom. As we build a bridge between beast and byte realms, this review serves as a resource for envisioning novel AI applications in zoological research that have not yet been explored.

**Keywords:** Animal science; Data extraction; Classification model; Behavior analysis; Biomolecular sequences analysis

## INTRODUCTION

Artificial intelligence (AI) stands at the forefront of modern scientific innovation (Wang et al., 2023a). Its research applications range from medical diagnostics (Moor et al., 2023) to climate tracking (Gore, 2022), with the scope of AI research expanding continuously. Of note, AI is making particularly significant strides in zoological research (Romero-Ferrero et al., 2019).

One challenge of zoological research, a discipline focused

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on animal classification, behavior, physiology, development, genetics and evolution, disease modeling, and paleozoology, is the management and interpretation of extensive and complex datasets. The rapid emergence of advanced AI techniques, such as machine learning (Jordan & Mitchell, 2015) and, in particular, deep learning (Hinton et al., 2006), as well as the emergence of big data, has marked the beginning of an era of intelligent data-centric zoological research.

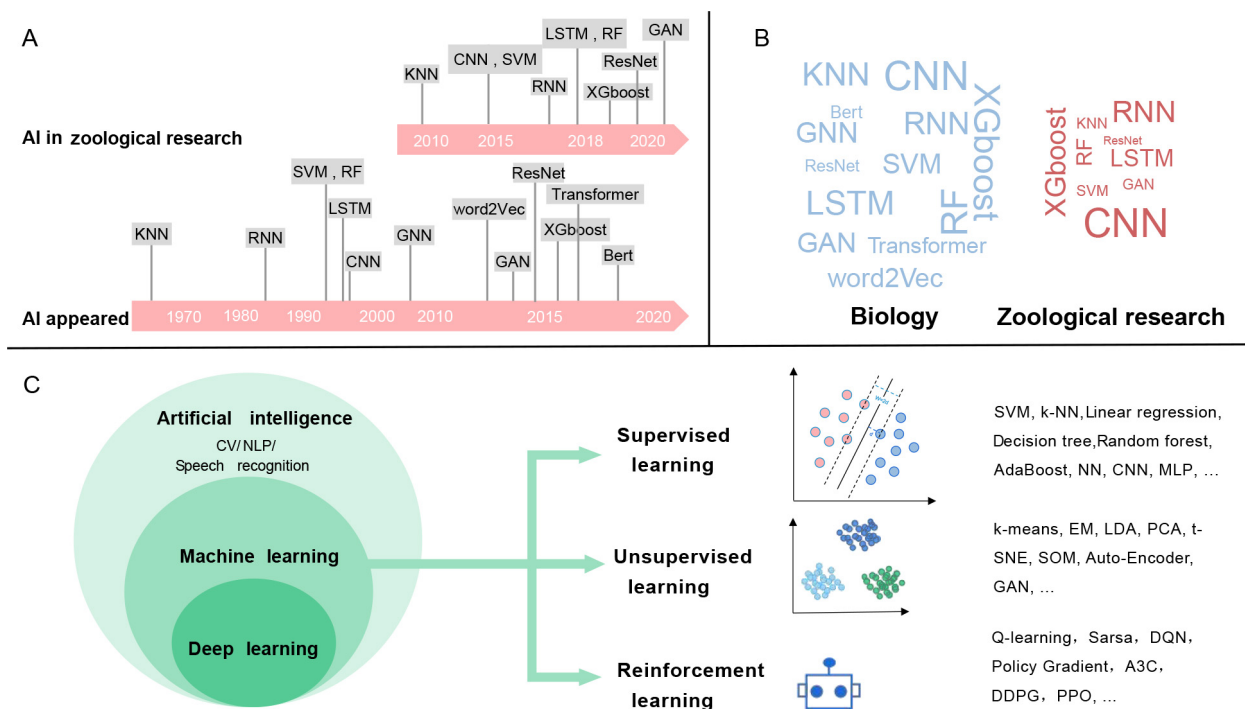
Although AI has been popular for some time, its incorporation into zoological research has not kept pace with its application in other biological fields (Figure 1A, B; Supplementary Table S1). Thus, the question arises as to why AI technologies have not been promptly adopted in animal research. A possible factor for the lack of application may be the inefficiency of computational resources and scarcity of expansive zoological datasets. Additionally, zoologists may lack the foundational knowledge required to understand and implement these approaches, creating uncertainty regarding the selection of models suitable for their objectives. Moreover, the rapid and continuous evolution of complex AI model architectures, like Bidirectional Encoder Representations from Transformers (BERT) (Devlin et al., 2019), make it challenging for zoological researchers to stay current. As access to advanced computational tools and comprehensive zoological datasets expands, it may pave the way for broader adoption of these algorithms in mainstream research. Nevertheless, unfamiliarity with these techniques persists among many zoologists, necessitating a foundational understanding of when, why, and how to employ these methods, as well as what type of data is suitable for their application.

In this review, we present an introduction to AI and its primary tasks, elucidating the key models, datasets, and challenges faced. We also explore the intersection where beasts meet bytes, examining how AI applications are

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\*Corresponding author, E-mail: [chern@cqnu.edu.cn](mailto:chern@cqnu.edu.cn)



**Figure 1** Branches and applications of AI

A: Timeline of various AI models and their applications in biological and zoological research. B: Word cloud charts displaying counts (Supplementary Table S1) of different AI models used in biological and zoological research, represented after  $\log_2$  transformation. C: Branches of AI, addressed tasks, and representative models. AdaBoost: Adaptive Boosting; A3C: Asynchronous Advantage Actor-Critic; BERT: Bidirectional Encoder Representations from Transformers; CNN: Convolutional Neural Network; CV: Computer Vision; DDPG: Deep Deterministic Policy Gradient; DQN: Deep Q-Network; EM: Expectation Maximization; GAN: Generative Adversarial Network; GNN: Graph Neural Network; KNN: K-Nearest Neighbors; LDA: Latent Dirichlet Allocation; LSTM: Long Short-Term Memory Network; MLP: Multi-Layer Perception; NLP: Natural Language Processing; NN: Neural Network; PCA: Principal Component Analysis; PPO: Proximal Policy Optimization; ResNet: Residual Neural Network; RF: Random Forest; RNN: Recurrent Neural Network; SOM: Self-Organizing Map; SVM: Support Vector Machine; t-SNE: t-distributed Stochastic Neighbor Embedding; XGBoost: Extreme Gradient Boosting.

revolutionizing diverse areas of zoological research. By analyzing real-world case studies and predicting future directions, we offer a comprehensive overview of the role of AI in deepening our understanding of the animal kingdom and the potential fields it may unlock in the coming years.

## ARTIFICIAL INTELLIGENCE

### AI and its primary tasks

AI was first defined by Stanford Professor John McCarthy in 1955 as a “the science and engineering of making intelligent machines” (Shabbir & Anwer, 2018). Machine learning, a fundamental branch of AI, is characterized by the capability of systems to autonomously learn from large datasets (de Souza Filho et al., 2020). Machine learning attempts to utilize experience, usually in the form of data, to improve model performance and the process of learning (Sarker, 2021). Therefore, machine learning research primarily focuses on the development of algorithms that generate models from data, termed “learning algorithms”. In the field of zoology, machine learning is helping to shed light on tasks such as species classification, behavior identification, animal population size prediction, bird sound recognition, and nonhuman animal language learning (Layton et al., 2021; Norouzzadeh et al., 2018). These specific tasks are broadly categorized into three types of machine learning, differentiated by their respective data training approaches: supervised, unsupervised, and reinforcement learning (Dönmez, 2013) (Figure 1C).

Supervised learning, one of the most widely used machine learning methods, relies on explicit datasets labeled by experts (Jiang et al., 2020). Supervised learning algorithms build models to identify relationships within a set of feature-label pairs, utilizing the label, also known as the target, for training the system (Li, 2017c). These algorithms fall into two main categories: classification (discrete modeling) and regression (continuous modeling). Both categories are predictive modeling techniques, differing only in their target (response) variables. In classification, the target variable is discrete and takes the form of categories (class labels). For example, animal species identification (Binta Islam et al., 2023), i.e., species classification, relies on learning from diverse data types, such as images, footprints, sounds, and videos, collected from various animals. More importantly, these data are manually annotated with labels indicating the species to which each sample belongs, with the labels corresponding to a predefined list of species. In this task, a model is trained to predict the species name when presented with new input data, such as animal photos. In contrast, in regression tasks, the target variable is continuous rather than discrete. For example, predicting the weight of cultivated cattle constitutes a continuous regression analysis, as the target variable, weight, is continuous.

Unsupervised learning (Li, 2017a) analyzes and clusters unlabeled datasets. Unlike in supervised learning, the inputs in this approach are usually raw data without available labels. These algorithms uncover hidden patterns in data without

requiring human intervention, thus termed “unsupervised”. Unsupervised learning models are used for three main tasks: clustering algorithms, which aim to discover unknown subgroups in unlabeled data based on their similarities or differences; dimensionality reduction techniques, which aim to minimize the dimensionality of data by discarding redundant or non-task-relevant information; and anomaly detection, which aims to identify observations that may have originated from different data generation processes. For example, application of the clustering task has enabled researchers to uncover the social structures within jackdaw populations by analyzing unlabeled data of visitation times of each individual (Valletta et al., 2017).

Reinforcement learning (Li, 2017c) involves a family of algorithms that typically operate sequentially. These algorithms are trained through interactions between agents and the (virtual) environment and applied to tasks where learning depends on executed actions and resulting consequences. A notable success is the AlphaGo computer program (Wang et al., 2016), which outperformed human players based on its integration of deep neural networks and reinforcement learning techniques. Frankenhuis et al. (2019) have advocated for the broader application of reinforcement learning methods in behavioral ecology to address the challenge of inferring the unknown reward functions of agents and to explore how biological mechanisms tackle developmental and learning problems.

In addition, AI tasks can also be classified based on the type of input data they process. The three typical subfields include computer vision (CV), natural language processing (NLP), and multi-modal learning. In the field of CV, the primary types of input data include images (e.g., grayscale, color, and binary images) and three-dimensional (3D) representations (e.g., point clouds (Liao et al., 2021)). In the field of NLP, the main data types include text data, speech data (e.g., voice and sound recordings), and time-series data (e.g., motion trajectories captured over time). In contrast, multi-modal learning (Lahat et al., 2015) integrates information from various data sources, ranging from CV to NLP and including images, text, and voice recordings. This integrative approach affords a richer data representation and more effectively captures relationships, thereby enabling a more complex and comprehensive analytical understanding.

CV seeks to automate tasks that the human visual system can perform and is concerned with the automatic extraction, analysis, and understanding of useful information from a single image or a sequence of images (e.g., videos). CV involves the development of a theoretical and algorithmic basis to achieve automatic visual understanding (Farahbakhsh et al., 2020). In this field, typical tasks (Chai et al., 2021) include image classification, retrieval, object detection, semantic segmentation, instance segmentation, object localization, action recognition, and object tracking, among other more specific tasks. Image classification (Lorente et al., 2021) is a fundamental task in CV that aims to categorize an image as a whole under a specific label. When the classification becomes highly detailed or reaches instance-level, it is often referred to as image retrieval (Chen et al., 2023b), which also involves the identification of similar images within a large database. Object detection (Zou et al., 2023) aims to detect and locate objects of interest within an image or video. Object localization focuses on locating an instance of a particular object category in an image, typically by specifying a

tightly cropped bounding box centered on the instance. In the literature, “object localization” refers to locating one instance of an object category, whereas “object detection” focuses on locating all instances of a category in a given image (Chai et al., 2021). Semantic segmentation aims to categorize each pixel in an image into a class or object, producing a dense pixel-wise segmentation map where each pixel is assigned to a specific class or object. Instance segmentation involves identifying and separating individual objects within an image, including detecting the boundaries of each distinct object of interest and assigning a unique label to each one. CV is skilled at handling various scenes related to images and videos.

NLP enables a computer system to automatically process and analyze sequence data, even extracting latent information by understanding the syntax in sequences, which is natural for humans (Young et al., 2018). Notably, NLP can capture dense vector representations, known as feature embeddings, from raw sequence data (Pilehvar & Camacho-Collados, 2021). Based on these feature representations, various language models have been created for downstream NLP tasks (Young et al., 2018). Within the context of zoological research, several closely related NLP tasks are commonly applied, including tokenization (Sodhar et al., 2020) for text data processing, text classification for video recognition (Xu et al., 2016), and language modeling for text or gene sequences. With advancements in deep learning models, NLP has the potential to revolutionize research in the zoological domain.

### Core models of AI

This subsection provides an overview of deep learning from various perspectives, including main concepts, architectures, and computational tools. The aim is to highlight the most important aspects of deep learning and serve as an instructive guideline for zoologists seeking to utilize this tool.

Due to its extraordinary learning capabilities, deep learning technology, which originated from artificial neural networks, has become a hot topic in the context of AI, with wide application in various areas such as CV, NLP, and speech recognition. Notably, between 2018 and 2021, the number of publications on neural network algorithms has shown a five-fold increase (Shine & Murphy, 2022).

AI models are broadly categorized into shallow or deep learning models based on the number of linear or non-linear transformations the input data undergo before yielding an output (Ahmad et al., 2018). Shallow models typically convert inputs once or twice before transmitting outputs, while deep models, derived from conventional neural networks, commonly convert inputs multiple times (Meir et al., 2023). As a result, deep models can learn more complex patterns, thereby facilitating end-to-end learning without the need for manual feature engineering and exhibit robust performance in CV and sequential data analysis tasks. The introduction of backpropagation (BP) algorithms for artificial neural networks (commonly referred to as neural networks) in the 1980s ushered in an era of machine learning dominated by statistical models (Janiesch et al., 2021), which continues to this day. In the 1990s, challenges such as overfitting and slow training speed in artificial neural networks led to the proposition of various other shallow machine learning models, including support vector machines (SVM), boosting techniques, and maximum entropy methods (e.g., logistic regression) (Xu et al., 2021). SVM and boosting are examples of hidden nodes

rather than models (e.g., logistic regression) that utilize hidden nodes. Geoffrey Hinton, along with Yoshua Bengio and Yann LeCun, has been a persistent advocate for the advancement of neural networks, playing a significant role in the development of a practical and feasible deep learning framework (Wang & Duan, 2021).

The effectiveness of machine learning algorithms is highly dependent on the integrity of the input data representation. Therefore, feature engineering has long been an important research area in machine learning, aiming to extract features from raw data with considerable human investment. In contrast, deep learning algorithms automate the feature extraction process, thus reducing reliance on extensive human labor and domain expertise to extract salient features. These algorithms possess a multi-layer data representation architecture, with the first layer extracting low-level features and the last layer extracting high-level features (Wang & Duan, 2021). Due to its considerable success, deep learning has emerged as a prominent research trend. In this context, convolutional neural networks (CNNs), recurrent neural networks (RNNs), and pretrained foundation models (PFMs) have been increasingly employed in zoological research.

Within the field of deep learning, CNNs are the most commonly used algorithms, with extensive application in image recognition, speech recognition, and NLP. The three principal advantages of CNN are equivariant representation, sparse interaction, and parameter sharing. Unlike traditional fully connected networks, CNNs leverage shared weights and localized connections to fully exploit two-dimensional (2D) input data structures, such as those found in image data. This operation employs a very small number of parameters, which simplifies the training process and accelerates network speed. This concept mirrors the functioning of cells in the visual cortex, as elucidated by Alzubaidi et al. (2021), where each unit is responsive to only a subset of the visual field, thereby capturing spatial localities within the input similar to the application of localized filters. A common type of CNN, akin to a multi-layer perceptron, features numerous convolutional layers preceding the subsampling (pooling) layer and concluding with a fully connected layer (Figure 2).

The high performance achieved by CNN architectures in challenging benchmark task competitions indicates that innovative architectural concepts and parameter optimization can improve CNN performance in various visually related tasks (Khan et al., 2020). The exploration of grid topology data (image and time-series data) by LeCun et al. (1989) marked the initial recognition of the capabilities of CNNs. Since 2012, different innovations have been proposed regarding CNN architecture. The performance improvements in CNNs can primarily be attributed to the reconstruction of processing units and design of new modules. With the introduction of AlexNet (Krizhevsky et al., 2017) and its exceptional performance on ImageNet datasets, the application of CNNs has become increasingly popular. The development of the Inception module by the Google team, characterized by its split-transform-merge strategy, marked a substantial advancement in CNN architectures. Its novel introduction of intra-layer branching facilitated feature extraction across varying spatial dimensions. In 2015, ResNet revolutionized CNN training by introducing residual connections (He et al., 2015), a concept incorporated in many subsequent networks, including Inception ResNet, wide residual networks, and ResNext. Similarly, certain architectures, including wide residual

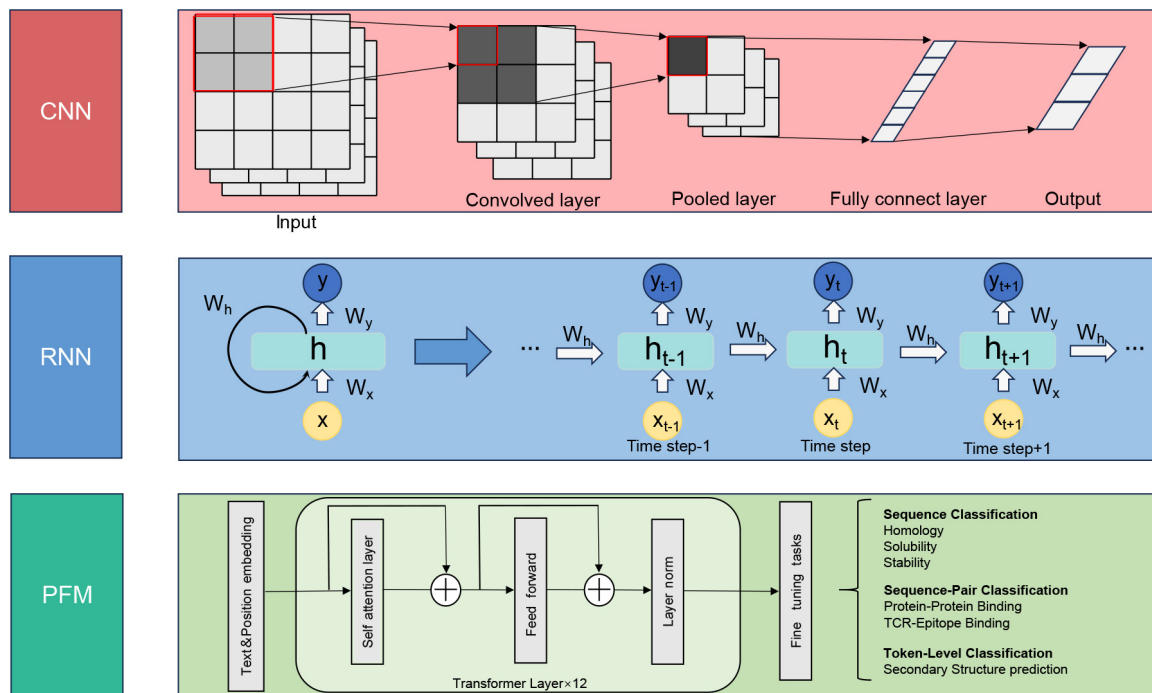
networks, Pyramid Nets, and Xception, have introduced multi-layer transformations, implemented through additional cardinality and increased width.

Typical deep CNN models, in addition to a fully connected layer (sometimes not included because of Global Average Pooling), also include convolutional and pooling layers, used to extract meaningful features from locally associated data sources and reduce the number of parameters, respectively (Khan et al., 2020) (Figure 2). Compared to other methods, the minimal preprocessing requirements of CNNs have solidified their status as the de-facto standard computation framework in CV. The achievements of CNNs have garnered widespread attention, both inside and outside academia, leading to the proliferation of diverse CNN models. For instance, the partialS/HIC model (Xue et al., 2021), which is based on a CNN for image processing, addresses the increasing demand for scanning tools capable of tracking in-progress evolutionary dynamics. Similarly, the DeepBehavior toolbox (Arac et al., 2019), which integrates many different CNNs, can automatically analyze animal behavior from both video and 3D image data. The landscape of CNN-based frameworks includes ResNet, MobileNet, DenseNet, ShuffleNet, EfficientNet, R-CNN, and YOLO (Zhu & Zhang, 2018). Among them, YOLO is an advanced algorithm for object detection, and includes different versions such as YOLOv2, YOLOv3, YOLOv4 (Bochkovskiy et al., 2020), and YOLOR (Wang et al., 2021). Each algorithm designed for object detection has the capability to identify objects both in real-time and with high accuracy.

RNNs, designed to handle sequential data (e.g., text, speech, and time series data), are commonly employed in the field of deep learning (Figure 2), including speech processing and NLP (Lipton et al., 2015). RNNs learn the features of time series data by memorizing previous inputs in the internal state of NNs. They can also predict future information based on past and present data but struggle to learn long sequences structures due to the vanishing or exploding gradient issue. Long short-term memory (LSTM) (Staudemeyer & Rothstein Morris, 2019) networks and their variants, such as the gated recurrent unit (GRU) networks (Chung et al., 2014), have resolved the gradient issue using various gates that control how information flows. These algorithms can be used in fields requiring the analysis of sequential data and the prediction of future events based on present data. Research in NLP frequently addresses time series data, analogous to that encountered in zoology, such as text, sound recordings, and sequence data. To capture the positional dependencies inherent in sequential data and retain abundance information from raw data, several deep learning-based models have been developed. RNN-based models (like RNN (Rumelhart et al., 1986), LSTM (Hochreiter & Schmidhuber, 1997)) and transformer-based models (Vaswani et al., 2017) (like BERT) have proven effective in automatically modeling sequential data and conducting downstream task prediction and analysis.

Transformer-based models are fundamentally structured around the attention mechanism and its derived framework, multi-head attention (Choi & Lee, 2023). Leveraging this core architecture, transformer-based models can overcome the limitations of RNN models, which cannot parallelize input processing across all time steps, while still effectively capturing the positional dependencies inherent in sequential data in tasks such as language translation, text summarization, image captioning, and speech recognition.





**Figure 2 Concise architectures of three deep learning models**

Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Pretrained Foundation Models (PFM).

The transformer includes encoder and decoder structures for processing sequence inputs and generating corresponding outputs, respectively (Choi & Lee, 2023). The architectural variant BERT, which only incorporates the encoder structure, employs random sequence masking during its pre-training tasks, leading to superior outcomes in protein 3D structure prediction (Lin et al., 2022b) and single-cell annotation (Yang et al., 2022).

Pretrained foundation models (Zhou et al., 2023) are essential and significant components of AI in the era of big data. These models demonstrate enhanced proficiency in multi-task learning with large-scale datasets and exhibit increased efficiency during fine-tuning for targeted, smaller-scale tasks, resulting in rapid data handling capabilities (Bommasani et al., 2021) (Figure 2). The most famous application among them is ChatGPT, a conversational model derived from the generative pre-trained transformer architecture developed by OpenAI (Gozalo-Brizuela & Garrido-Merchan, 2023). ChatGPT applies reinforcement learning from human feedback (RLHF) (Bai et al., 2022), a promising approach for aligning large language models with human intent, i.e., pretrained language models (Wulff et al., 2023). Many open-source pretrained language models are currently available, operable on individual computing systems and trainable on private datasets, including Llama, Alpaca, Vicuna, and Falcon models (Zhang et al., 2023). Given their success (Wang et al., 2023b) in various general-domain NLP tasks, these open-source large language models exhibit significant potential for application when fine-tuned using knowledge-based instruction data.

Inspired by the success of pretrained language models in NLP, pre-trained visual models in the field of CV have also achieved great success. These models are pre-trained on massive image datasets and can analyze image content and extract rich semantic information. Furthermore, multi-modal visual models like CLIP (Radford et al., 2021) and ALIGN (Cohen, 1997; Lahat et al., 2015) use contrastive learning to

align textual and visual information. This alignment allows the pre-trained models to apply learned semantic information to the visual domain, thereby facilitating efficient generalization in downstream tasks, including zoological applications.

Generative models and contrastive learning are two other important types of models. Generative models gained popularity after the introduction of generative adversarial networks (GANs) in 2014, which formed the foundation for many subsequent architectures, including CycleGAN (Zhu et al., 2017), StyleGAN (Karras et al., 2019), and DiscoGAN (Kim et al., 2017). Unlike generative models, contrastive learning is a discriminative approach that aims to group similar samples closer together and diverse samples farther apart (Jaiswal et al., 2021). To achieve this, a similarity metric is used to measure the closeness of two embeddings. Self-supervised learning, a type of unsupervised learning (Wang, 2022), integrates both generative and contrastive approaches. Notably, it utilizes unlabeled data to learn underlying representations, thereby avoiding the labor-intensive task of data labeling. Thus, this approach offers the potential for better utilization of unlabeled data in zoological research.

Given that deep learning has proven more effective in data extraction, feature representation, and prediction than non-deep learning models, our emphasis is on discussing deep learning models used in zoological research and explaining why they are more effective compared to non-deep learning models, especially when dealing with unstructured data such as images, text, videos, and sequence data. Furthermore, while supervised task is frequently discussed in this review due to their relevance to species classification and identification (fundamental concerns in Zoology), we also address unsupervised and reinforcement learning.

### Datasets in zoological research

A variety of datasets are available for research in zoology, each tailored to specific tasks, as summarized in Supplementary Table S2. These datasets primarily

encompass text and image data. Text data can be processed using a range of models, such as RNN, transformer, and pretrained foundation models, depending on the specific task requirements. Image data, including videos, are compatible with models developed for CV tasks. Among these datasets, the Paleobiology Database, maintained by an international consortium of non-governmental paleontologists, is a publicly accessible repository of paleontological data (Alroy et al., 2008). The AP-10K dataset (Yu et al., 2021) represents the first comprehensive resource for general animal pose estimation, featuring 10 015 images from 23 animal families and 54 species, with high-quality keypoint annotations. This highly versatile dataset is suitable for supervised, self-supervised, semi-supervised, and cross-domain transfer learning, as well as intra- and inter-family domain analyses, with annotation files provided in Common Objects in Context (COCO) format. The KaoKore dataset, established by the ROIS-DS Center for Open Data in the Humanities, comprises a curated collection of facial expressions and has been publicly accessible since 2018 (Tian et al., 2020).

Complex unstructured data in zoological research, including images, videos, sounds, and text, present considerable challenges for AI application. Addressing these challenges often requires expert selection of appropriate models and significant data preprocessing efforts. The following sections provide detailed discussion on AI models tailored for different data types and tasks (Supplementary Table S3), as well as their specific processing procedures. This information should help researchers in selecting models best suited for their specific data and research goals.

## AI IN ANIMAL CLASSIFICATION AND RESOURCE PROTECTION

The rapid identification and classification of wild animals is critical for the categorization and protection of biological resources. However, such tasks typically require extensive labor and time investment from experts to process data (Vélez et al., 2022) and manually extract information from field-captured photographs (Kulkarni et al., 2020). To handle these challenges, AI algorithms, especially deep learning models effective in graphic identification studies, have been increasingly applied for the automatic identification of wildlife (Figure 3A). Previous research using deep neural networks (DNNs) to automatically identify, count, and describe wild animals in images captured by motion-sensor cameras not only reduced human labor costs but achieved a high identification accuracy of 96.6%, exceeding that of expert identification (Norouzzadeh et al., 2018). Moreover, such innovative approaches demonstrate that deep learning techniques, in contrast with traditional methodologies for single-species classification, have marked advancements in the classification of multiple species, enhancing the versatility available to researchers in the field of animal resource studies. CNN algorithms have also been used to identify endangered animals in images captured by unmanned aerial vehicles, enabling non-invasive surveillance and protection (Kellenberger et al., 2018). Similar studies have likewise demonstrated success (Fergus et al., 2023; Tabak et al., 2019), highlighting the potential for AI to accelerate advancements in wildlife classification, re-identification, and biodiversity monitoring (Thalor et al., 2023).

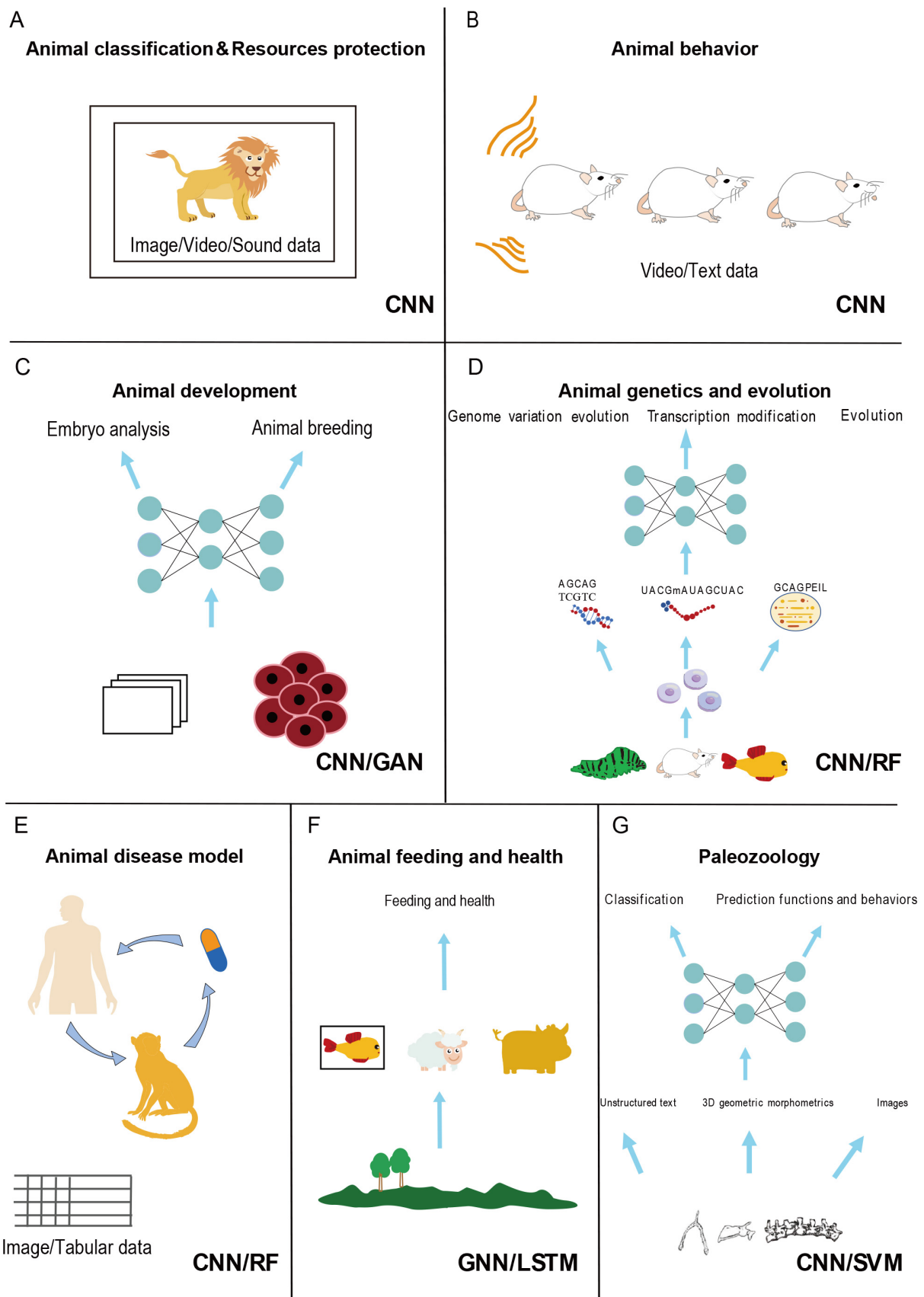
The conflict between human activity and wildlife is becoming ever more pronounced, manifesting in the extinction of

species and degradation of natural habitats. To alleviate these issues, there is an urgent need for effective management and monitoring of wildlife ecological preserves to reduce negative human-animal encounters. The development of DeepVerge, a CNN-based approach, represents a significant advance in this regard, enabling judicious planning of road construction and environmental management by governments. Notably, DeepVerge has shown a mean accuracy of 88% in the identification of positive indicator species in grassland ecosystems, a traditionally challenging task in wildlife resource surveys (Perrett et al., 2022). Nandutu et al. (2022) also employed CNN technology to analyze images captured from unmanned aerial vehicles for the detection of wildlife fences along roadsides, thereby reducing the frequency of human-animal encounters and enhancing the protection of wildlife from traffic-related hazards.

Furthermore, AI models have the ability to collect wildlife images from social media platforms to expand biodiversity preservation efforts, thereby compensating for the scarcity of corresponding data from traditional wildlife monitoring techniques (Foglio et al., 2019). In addition, automatic AI-assisted analysis of aerial images can facilitate accurate counting of various species, such as elephants and dolphins (Singh et al., 2023). These models generally outperform conventional analytical methods, primarily due to their superior capacity for extracting features from images, as well as their regularization and denoising capabilities. These strengths facilitate their application across distinct categories of images, including both wildlife and aerial photographs, irrespective of apparent disparities in image type.

Insect taxa are numerous and characterized by fine-grained distribution patterns. (Høye et al., 2021). Traditional insect detection methods face challenges in performance, particularly when identifying small pests, due to a lack of adequate learning samples and models. To address this, Xiang et al. (2023) developed Yolo-Pest, a CNN-based model optimized for the effective detection of small target pests, which showed significant improvement in performance compared to existing methods when tested on the Teddy Cup pest dataset. Tsetse flies serve as important vectors of human disease in Africa. Geldenhuys et al. (2023) developed a CNN-based method for classifying tsetse fly images and precisely predicting wing landmarks to facilitate vector identification and control. Additionally, Lee et al. (2023) developed a deep learning-based automated object detection technique to identify mosquito species from image data, thereby reducing manual labor in the field.

However, it is important to note that the application of AI in the classification and protection of animal resource is still in its early stages. Although advanced DNN and CNN models have yielded good results in analyzing wildlife pictures, the adaptability and robustness of AI algorithms in dealing with variations in image quality and lighting conditions still require improvement. Classification accuracy typically diminishes when species are recorded live within their natural environments (Van Horn et al., 2017; Wu et al., 2019). Consequently, future work should focus on these issues and refine AI models for application in diverse natural environments. Moreover, wildlife data covers not only images but also an abundance of text and voiceprint data, which are inherently sequential and more amenable for analysis using transformer-based frameworks, such as BERT (Khan et al., 2022). Although the use of CNNs for classifying bird species



**Figure 3 Application of AI across different fields**

Each panel highlights examples of input data type, model type, and applied species of AI. A: Animal classification and resource protection, B: Behavior and neuroscience, C: Development, D: Disease models, E: Breeding and feeding, F: Evolution and genetics, and G: Paleozoology. CNN: Convolutional Neural Network; GAN: Generative Adversarial Network; GNN: Graph Neural Network; LSTM: Long Short-Term Memory Network; RF: Random Forest; SVM: Support Vector Machine.

based on raw sound waveforms has achieved suboptimal accuracy (Bravo Sanchez et al., 2021), the application of transformer-based approaches, though presently limited (Supplementary Table S3), holds considerable promise for future research.

## AI IN ANIMAL BEHAVIOR

### Animal behavior and neuroscience

Animal behavior is critically related to neural activity, neurological function, and cognitive states. Research has uncovered the mechanisms that govern a variety of complex animal behaviors, including those related to feeding (Shafiullah et al., 2019), anxiety, and mating (Moulin et al., 2021), as well as the analysis of daily behaviors (Liu et al., 2022) and recognition of behaviors based on facial expressions (Liu et al., 2023). However, the core problem lies in the extraction of meaningful information from the wealth of data on animal behavior within the context of neuroscience, propelled by advancements in experimental techniques (Bath et al., 2014; Scaplen et al., 2019; Svensson et al., 2018). Such data are often presented as high-dimensional time series (Scaplen et al., 2019), video recordings (Liu et al., 2022), still images, and 3D image data. These data types are complex, high-dimensional, and sometimes unstructured, rendering them unsuitable for analysis using traditional methods (Figure 3B).

In comparison, deep learning-based models are effective in extracting features and representations from unstructured data. For instance, DeepLabCut, using deep learning transfer techniques, presents a novel approach for estimating the gestures of unlabeled objects, and has produced outstanding results with minimal training data (Mathis et al., 2018). The CNN-based DeepBehavior toolbox enables the automatic analysis of animal behavior data, including both video and 3D image data and has proven effective in neuroscientific investigations of five distinct mouse behaviors (Arac et al., 2019). Coffey et al. (2019) recently developed DeepSqueak, an automatic vocalization analytical framework trained and validated using a comprehensive dataset of mouse and rat vocalizations, which revealed that the grammatical structure of these vocalizations was related to social behaviors, especially mating behaviors. Similarly, Graving et al. (2019) developed DeepPoseKit, a deep learning model adept at the rapid and accurate analysis of animal poses, a critical component for behavioral estimation with important implications in neuroscience research. Sainburg and Gentner (2021) developed CNN and RNN-based computational neurobehavioral models to elucidate the physiological characteristics of animals, especially in the context of acoustic communication. In addition to deep learning techniques, Klibaite et al. (2017) also established a machine learning-based Gaussian mixture model to automatically extract information from animal behavior video recordings, supporting studies in the field of neuroscience

The study of animal behavior, informed by neural activity and complex interactions, can guide the design and construction of deep network models (Richards et al., 2019). This research draws connections between animal neurology and behavior and the foundational principles inherent to reinforcement learning, highlighting the parallels in strategic optimization, task resolution, and reward allocation within these domains.

### Animal feeding behavior monitoring

Feeding behavior is a key concern in animal behavior and a crucial factor for health and survival. Achour et al. (2020) used four CNNs to analyze the feeding behavior of cows. Their analytical framework was designed to recognize individual cows and distinguish whether they were eating or standing in a feedlot area, as well as whether there were different food categories in the feedlot. In addition, Chen et al. (2020) developed a video-based deep learning method to identify piglet feeding behavior and calculate feeding durations based on multiple one-second feeding and non-feeding events obtained from video footage. The CNN architecture was used to extract spatial features, which were then fed into a LSTM framework to extract temporal features. These features were then propagated through a fully connected layer, and a Softmax classifier was applied to categorize the one-second segments into feeding or non-feeding events, demonstrating excellent sensitivity (98.8%), specificity (98.3%), and accuracy (95.9%) in identifying feeding behavior.

Data generated in animal husbandry, including feeding data, physical characteristics, and health conditions, can be used to predict other animal characteristics, such as weight and growth trajectories. He et al. (2021) used LASSO regression and two machine learning algorithms, random forest and LSTM network, to predict the weight of pigs aged 159 to 166 days. The predictions were made in four scenarios: individual-specific prediction, individual and population-specific prediction, breed-specific individual and population-specific prediction, and population-specific prediction. For each scenario, four models were developed, and their predictive performance was evaluated using the Pearson correlation coefficient, root mean square error, and binary diagnostic tests. Notably, they successfully predicted pig weights based on feeding conditions and yielding favorable outcomes, confirming the feasibility of using predictive methods to determine later-stage characteristics of animals. Taylor et al. (2023) used machine learning to estimate the growth trajectories of individual pigs based on their weight, subsequently validating trajectory predictions using root-mean-square deviation scores. The findings revealed that, on average, the random forest model exhibited the most accurate predictions, achieving the best score of 2.00 kg per pig and the worst score of 2.45 kg per pig, outperforming traditional approaches and showing considerable prediction potential.

Using AI models, it is also possible to predict feed supply stages and initiate adjustments to avoid feed shortages, as well as to predict delivery behavior to reduce the mortality rate. Shafiullah et al. (Shafiullah et al., 2019) assessed various machine learning algorithms, including SVM, random forest, XGBoost, and neural networks, to predict shortages in spring forage by analyzing changes in cow feeding behavior indicative of potential feed insufficiency. Turner et al. (2023) developed deep learning models to identify the behavior of ewes during childbirth and postpartum licking, using data obtained from accelerometer sensors located on the neck of the sheep. Behavior labels derived from video recordings and an LSTM model were then used to classify different behaviors. The model achieved an accuracy of 84.8% and a weighted F1 score of 0.85 in identifying birthing and licking actions, effectively differentiating between parturition behaviors. This provides a critical framework for prompt intervention during challenging births, potentially decreasing neonatal lamb mortality.



Although AI models have been successfully utilized in feeding behavior monitoring, capable of processing different forms of data, it is important to note that CNNs and their variants play dominant roles in this realm (Supplementary Table S3). Given their sequential nature, time series and video recording data may be better processed using transformer-based architectures. The pre-trained large language models underpinning BERT (homologous transformer architecture) have already set new benchmarks in sequence-dependent bio-research (Khan et al., 2022; Lin et al., 2022). Hence, we propose that future studies, particularly those involving time-series analyses of continuous data from animal vocalizations, locomotion positions, and text data, may benefit from the utilization of language models, rather than solely relying on CNNs.

## AI IN ANIMAL DEVELOPMENT

Advancements in AI within developmental biology predominantly center on the application of CV and machine learning algorithms for the automated processing of images, particularly embryonic images (Figure 3C). Assessment of embryo quality is crucial for improving pregnancy rates following *in vitro* transfer. Although morphological analysis remains the standard for evaluating embryo quality, it is subject to variation based on the expertise of the evaluator (Rocha et al., 2017). In contrast, AI methods enable systematic and automatic embryo quality evaluations, demonstrating enhanced robustness compared to conventional assessments. Researchers initially developed a computational model using dynamic Bayesian networks and machine learning to understand the regulatory networks governing cell differentiation processes in multicellular organisms, with a focus on *Caenorhabditis elegans*, and reported significant enhancements in inferential accuracy through the integration of interaction data from various species (Sun & Hong, 2009). Following this, the automated DevStaR system was developed, employing CV and SVM to provide rapid and accurate measurements of embryonic viability and high-throughput quantification of developmental stages in *C. elegans*, a principal model organism in developmental and behavioral studies (White et al., 2013).

Fish embryo models are commonly used for assessing the efficacy and toxicity of chemicals. Genest et al. (2019) automated this process by classifying fish embryos based on the presence or absence of spinal malformations using 2D images, feature extraction based on mathematical morphology operators, decision trees, and random forest classifiers. Quantitative analysis of cerebral vasculature is crucial for understanding vascular development. Chen et al. (2023a) developed a deep learning method to analyze cerebral vasculature in transgenic zebrafish embryos. Using 3D light-sheet imaging and FE-Unet to enhance 3D structures, they transformed incomplete vascular structures into continuous forms, allowing for the accurate extraction of eight key topological parameters. Polarization of mammalian embryos at the correct time is crucial for development. Shen et al. (2022a) developed an automated stain-free detection method for detecting embryo polarization using a deep CNN binary classification model, achieving an accuracy of 85% and significantly outperforming human volunteers trained on the same data (61% accuracy). In addition, Qiu et al. (2021) introduced a deep learning pipeline for automating the segmentation and classification of high-frequency ultrasound

images of mouse embryo brain ventricles and bodies based on a volumetric CNN classifier, thus providing a powerful tool for developmental biologists.

In the industrial sector, integrating AI and animal development can facilitate the generation of offspring with ideal characteristics or improved performance to meet human needs. A critical component of this process involves the identification of parents exhibiting superior phenotypes for reproduction. Robson et al. (2021) implemented an automated system combining generative adversarial networks with a CV pipeline to extract phenotypic data from ovine medical images, achieving an accuracy of 98% and faster speed (0.11 s vs. 30 min), thereby greatly reducing processing time. The phenotypes identified using this approach can provide valuable insights to guide genetic and genomic breeding programs and benefit animal breeding. Furthermore, Rocha et al. (2017) developed a novel method for embryo analysis by combining a genetic algorithm and artificial neural network, which was applied to test features extracted from 482 bovine embryo images, achieving an accuracy of 76.4% compared with evaluations conducted by embryologists.

## AI IN ANIMAL GENETICS AND EVOLUTION

Recent advances in third-generation high-throughput sequencing and assembly technologies (Mao et al., 2021) have streamlined the acquisition of genomic, transcriptomic, and expression profiles in animals (Zhang et al., 2018). However, the challenge of processing huge multiomics data has created an urgent need for the application of AI technologies. This has significantly enhanced the efficiency of data analysis and elucidated previously difficult to observe biological phenomena (Badia et al., 2023; Gomes & Ashley, 2023). Notably, various machine learning techniques, such as random forest and gradient boosting, as well as deep learning approaches, such as CNN, DNN, and RNN, have been widely employed (Figure 3D) to study genetic variation, transcriptional modification, and evolutionary issues, primarily based on genomic and proteomic data.

### Genetic variation

Traditional genetic variation analyses (Durward-Akhurst et al., 2021; Mashayekhi & Sedaghat, 2023) often struggle to handle large-scale genomic data. In contrast, AI can rapidly and effectively process these vast datasets (Kaushik et al., 2021), offering greater precision in identifying meaningful mutation sites and expediting the inference of biological functions.

Next-generation sequencing has revolutionized genetic testing but has also produced considerable amounts of noisy data, necessitating extensive bioinformatics analysis for meaningful interpretation. The Genome Analysis Toolkit (GATK) has stood as the gold standard for reliable genotype calling and variant detection (Brouard et al., 2019; Lin et al., 2022a). However, the development of cutting-edge deep neural networks, such as DeepVariant, has shown exceptional accuracy in identifying genomic variations, from single nucleotide polymorphisms (SNPs) to indels (Yun et al., 2020). In comparison to GATK, DeepVariant showed a 2% reduction in data errors, highlighting its potential in the ever-evolving field of genomics (Lin et al., 2022). In addition, Babayan et al. (2018) employed a gradient boosting machine algorithm to extract sequence data from over 500 single-stranded RNA viruses and analyzed the evolutionary signals within them, resulting in the rapid identification of pathogens and their

potential hosts and vectors, thus providing new avenues for disease control and prevention. Furthermore, Layton et al. (2021) integrated genomic diversity with environmental relevance and a random forest model to identify vulnerable populations of Arctic migratory fish (migratory charr) and reconstruct population sizes and climate-related declines throughout the 20<sup>th</sup> century. This innovative approach revealed the impacts of climate change on species survival, providing important scientific support for the conservation and genetic breeding of Arctic ecosystems.

Deep learning models, including CNNs and RNNs, have been recently applied in animal omics analyses. Researchers have addressed challenges such as the detection of selective sweeps within mosquito populations (Xue et al., 2021) and identification of short viral sequences within metagenomes (Lee et al., 2021). Xue et al. (2021) devised partialS/HIC, a deep learning approach based on CNNs, to analyze the African mosquito genome, enabling detection of different stages and regions of selective sweeps and insecticide resistance, thus identifying adaptive loci critical for disease control. Additionally, Kaplow et al. (2023) explored the use of CNNs for elucidating genetic variations in enhancers and identifying associations between enhancers and phenotypes across various mammals. Furthermore, Jiang et al. (2023) developed RNN-VirSeeker, a deep learning method tailored to detect short viral sequences within pig metagenomes. Trained on 500 bp samples of known viral host RefSeq genomes, RNN-VirSeeker surpassed three established methods in testing, achieving superior performance in receiver operating characteristic curve (AUROC), recall, and precision, particularly for the CAMI gut metagenome dataset. These studies integrating AI with genomics not only lay the groundwork for understanding genetic variation within animal populations but also forge new pathways for linking genomic research with phenotypes.

### Transcriptional modification

Transcriptional modification (Li et al., 2017b), a complex process central to the regulation of gene expression, presents a challenge to traditional analysis due to its dynamic and complex nature. Deep learning models, which excel at handling large datasets and identifying modifications (Salekin et al., 2020), offer a powerful and efficient solution for transcriptional modification analysis in the era of big data. Luo et al. (2022) developed im6APred, an advanced model designed to predict N6-methyladenosine (m6A) sites—a pivotal RNA modification implicated in many biological processes (Zhu et al., 2020)—across a spectrum of mammalian tissues. The architecture of im6APred was grounded in the comprehensive assessment of seven distinct classification methods, including four traditional algorithms and three deep learning techniques, along with their integration. This ensemble approach enabled im6APred to ascertain the general methylation patterns on RNA bases and extend this knowledge to the entire m6A transcriptome across different tissues and biological environments, with increased prediction accuracy and robustness.

### Evolutionary issues

The integration of AI with omics data has proven efficacious in extracting vital features from such datasets, which are subsequently employed in the construction of phylogenetic trees for species classification and in the adaptive analysis of gene flow. Barrow et al. (2021) highlighted the potential of

machine learning algorithms, particularly the random forest model, in analyzing intraspecific diversity among Nearctic amphibians, integrating over 42 000 gene sequences across 299 species. Similarly, Derkarabetian et al. (2019) applied genomics to study species classification within arachnid taxa, such as *Metanonychus*, known for a high degree of population genetic structuring. Using three unified machine learning methods, namely, random forest, variational autoencoders, and t-distributed Stochastic Neighbor Embedding (t-SNE), they constructed a phylogenetic tree conducive to species delimitation, demonstrating effectiveness across diverse natural systems and taxa with different biological characteristics.

Deep learning techniques have also been applied in the study of animal evolution. Gower et al. (2021) introduced an innovative CNN-based approach that analyzes the genome to explore adaptive introgression in human evolution, particularly the process of adaptive gene flow. This approach, which aims to distinguish between genomic regions influenced by adaptive gene flow from those affected by neutral evolution or selective sweeps, has been successfully applied to the human genome dataset, achieving 95% accuracy in identifying candidate regions implicated in adaptive gene flow, thus offering insights into the evolutionary history of humans.

Deep learning approaches have also been successfully integrated with protein sequences. Li et al. (2018) introduced DNN-PPI, a deep neural network framework for analysis of protein interaction datasets from humans, mice, and other species, which showed excellent prediction accuracy and significant generalization ability. Its innovation lies in its ability to make predictions entirely from features automatically learned from protein sequences, thus avoiding the need to rely on complex biochemical information. These examples emphasize the advantages of AI in evolutionary studies, showcasing its proficiency in handling large-scale datasets, revealing hidden evolutionary patterns, and enhancing analytical efficiency.

### AI IN ANIMAL DISEASE MODELS

Animal disease models are essential for advancing our understanding of human pathologies and drug development. In the face of challenges associated with the automatic and effective processing of diverse data, various AI models have been adopted to process complex datasets related to animal disease (Figure 3E). Tree-based methodologies, including random forest and Extreme Gradient Boosting (XGBoost) models, are more adept at handling structured tabular data than popular deep learning models (Grinsztajn et al., 2022). Conversely, non-deep learning algorithms, such as logistic regression and SVM, are often employed for the modeling and analysis of structured data due to their simplicity in training. For example, Leung et al. (2019) analyzed amyloidosis in Indian-origin rhesus macaques by applying logistic regression to structured tabular data with 62 variables. After analyzing the model output, they identified significant factors associated with diagnoses of colitis, gastric adenocarcinoma, and endometriosis, along with clinical issues including trauma and pregnancies. Gardiner et al. (2020) utilized several machine learning models, including linear regression, XGBoost, random forest, k-Nearest Neighbors, and light gradient boosting, to extract information from gene expression and chemical structure data, predicting potential renal dysfunction induced by drugs in rats. These studies highlight the potential

of non-deep learning algorithms to effectively handle structured tabular data and benefit research on animal disease models.

As discussed above, deep learning techniques are more suitable for unstructured data, as demonstrated across various studies. Bouteldja et al. (2021) leveraged CNN models to analyze whole-slide images from mouse models of disease, including unilateral ureteral obstruction, adenine-induced kidney disease, renal ischemia-reperfusion injury, and nephrotoxic serum nephritis. Based on computational comparative pathology, Abduljabbar et al. (2023) utilized a CNN model trained on human samples to accurately assess immune responses in 18 vertebrate species. Li et al. (2023) used a ResNet-based toolkit to investigate active and depressive behaviors in mutant monkeys, serving as a disease model for Rett syndrome. Zhang et al. (2022) developed an enhanced YOLOv5 model algorithm to significantly increase the accuracy and efficiency of counting retinal ganglion cells in glaucoma research.

Although non-deep learning and deep learning algorithms are employed for various types of data, it is important to note that structured data often originate from raw unstructured data, such as chemical structures. This conversion, known as feature engineering (Verdonck et al., 2021), can lead to the loss of original information, potentially impairing the predictive accuracy of models. Additionally, gene expression and key variable datasets may be transformed or regarded as pseudo-sequential (Yang et al., 2022) or graph-structured data (Cao & Gao, 2022). Therefore, deep learning algorithms, with their inherent ability to fit unstructured data, may dominate in this research area. These algorithms offer enhanced precision, end-to-end manipulation of unprocessed data for the extraction of predictive outcomes, and more effective exploitation of the intrinsic relationships embedded within the data.

## AI IN ANIMAL BREEDING AND HEALTH

Traditional methods of recording animal behavior, size, weight, and feeding data to predict growth patterns and living habits require substantial manpower and material resources. Moreover, intensive efforts to optimize efficiency and output in animal husbandry can result in substantial social deprivation for livestock, leading to adverse effects on behavior and welfare (Neethirajan, 2021b). AI has the potential to enhance farm management and breeding practices by advancing the automation of anomaly detection, body condition evaluation, and disease diagnosis (Figure 3F). Such advancements can substantially reduce the burden of manual data analysis while increasing overall accuracy.

### Abnormal detection in breeding

Although conventional methods based on sensors are well established, they often fail to detect anomalies promptly due to the extensive coverage of farming facilities. In contrast, machine learning technology offers rapid, efficient, and contactless automatic recognition of individual animals for breeding farm management. Shen et al. (2020) developed a recognition method using the YOLO model to detect side view images of cows and a fine-tuning CNN for classification, achieving a recognition accuracy rate of 96.65%. Similarly, Li et al. (2017a) extracted shape feature descriptors from captured cow tail root images, employing four classifiers, namely linear discriminant analysis, quadratic discriminant

analysis, artificial neural network, and SVM, with the quadratic discriminant analysis and SVM classifiers demonstrating superior performance, obtaining an F1 score of 0.995 and the highest accuracy and precision, respectively. Additionally, Bakoev et al. (2020) used nine machine learning algorithms, including random forest and k-Nearest Neighbors, to assess pig limb conditions based on growth and meat characteristics, thus addressing the issue of leg weakness and lameness in pig farming.

With the increasing need to boost fishery productivity, AI models have been applied to aquaculture management to monitor fish growth and improve aquatic product quality. Chang et al. (2021) developed an intelligent cage farming management system, known as AIoT, to collect extensive data on fish and feed within the cage environment. They trained two deep learning-based object detectors, Faster-RCNN and YOLOv3, to specifically detect fish bodies and monitor growth and feeding conditions, thereby reducing feed waste, enhancing feed conversion rates, and increasing fish survival rates. The YOLO model is capable of tracking multiple objects in real-time within images, making it ideal for automated systems designed to monitor large populations in both aquaculture and fisheries. Fish classification is essential for quality control and population statistics. However, the task becomes challenging due to changes that occur when fish leave the water. Abinaya et al. (2021) implemented a deep learning model augmented with a naive Bayes classifier for fish classification, achieving better accuracy and robustness compared to original neural networks. Additionally, Liao et al. (2021) developed 3DPhenoFish to provide a more efficient and objective approach for semantic segmentation and extraction of 3D fish morphological phenotypes from point cloud data, which has implications in artificial breeding, functional gene mapping, and population-based studies in aquaculture and ecology.

### Animal health

AI technologies have also been applied to streamline animal healthcare by improving body condition assessment and disease diagnosis (Ezanno et al., 2021). Accurate body condition scoring is crucial for evaluating health and energy balance in cows, guiding dietary and reproductive management (Cockburn, 2020; Rodríguez Alvarez et al., 2019). Rodríguez Alvarez et al. (2019) developed a CNN-based model combined with transfer learning and ensemble modeling to assess body condition in cows from depth image features, achieving an accuracy of 82% within 0.25 units and 97% within 0.50 units of the real value. In addition, bluetongue disease represents a common infectious disease in ruminants. Gouda et al. (2022) utilized several algorithms, including logistic regression, decision tree, random forest, and feedforward artificial neural network, to predict the risk of bluetongue disease using seroepidemiological data, with the centralized machine learning model outperforming traditional methods. Wagner et al. (2020) used machine learning techniques, such as K-nearest neighbor regression, decision tree regression, Multi-Layer Perceptron, and LSTM, to detect subtle behavioral changes in dairy cows based on data from the previous day. Furthermore, AI algorithms have been applied to automatically monitor the health and emotional state of animals (Neethirajan, 2021a). Neethirajan (2021b) developed an AI model based on generative adversarial network architecture capable of analyzing different modes of



animal communication behavior and generating virtual conspecific companion videos to improve animal well-being. Such AI-driven approaches can successfully detect abnormal behavior and stress in animals, even before clinical symptoms appear.

## AI IN PALEOZOLOGY

The field of paleozoology, dedicated to the study of prehistoric life through fossil analysis, has traditionally demanded significant labor and time. In recent years, however, advancements in AI algorithms capable of learning, prediction, and automation have revolutionized this field by enhancing fossil analysis, species identification, and the extrapolation of functions and behaviors from fossil evidence (Figure 3G).

AI has been effectively applied for the classification of animal fossils based on both text and image data. For instance, in their study on marine invertebrates, Kopperud et al. (2019) used an automated pipeline based on supervised machine learning to extract observations of fossils and their inferred ages from unstructured text, achieving high accuracy compared to human annotators and greatly reducing the time required. In a broader study, Hoyal Cuthill et al. (2020) used a machine learning spatial embedding method to measure distance among 171 231 species and analyze the impacts of speciation and extinction based on an evolutionary decay clock. In regard to primates, AI has been utilized to infer behaviors from fossils based on species classification (Marcé-Nogué et al., 2020; Püschel et al., 2018). Püschel et al. (2018) applied machine learning classification methods to differentiate between various locomotor categories in primates, using both biomechanical and morphometric data. Similarly, Marcé-Nogué et al. (2020) used an SVM algorithm to classify primate fossils into broad ingesta-related hardness categories.

The application of deep learning algorithms for image data analysis has become increasingly prevalent in resolving classification issues related to animal fossils. CNNs have demonstrated considerable accuracy in the classification of modern and ancient bone surface modifications within multiple mammals (Dominguez-Rodrigo et al., 2020). Using both unsupervised and supervised AI algorithms, studies have achieved high accuracy (88%–98%) in classifying carnivore species based on 3D modeling and geometric morphometrics of tooth pits (Courtenay et al., 2021). Furthermore, deep CNNs have distinguished between theropod and ornithischian dinosaur tracks based on outline silhouettes, consistently demonstrating superior performance compared to human experts (Lallensack et al., 2022).

## CHALLENGES FOR USING AI IN ZOOLOGICAL RESEARCH

As discussed in the introduction, there is a lag in the adoption of AI in zoological research (Figure 1A, B). One reason for this delay is the unfamiliarity of zoologists with various models, coupled with the challenges arising from data format complexity, data insufficiency, and reliance on small sample learning tasks. Comprehensive zoological research includes complex unstructured data, spanning images, videos, sound recordings, text sequences, and protein structures, presenting significant challenges for AI model applications, requiring experts to select appropriate models for specific data types and, in some instances, expend additional effort in data

processing. Small sample learning is another common challenge, especially when studying specific species or ecosystems, with the extreme rarity of certain animal species posing considerable challenges in gathering adequate data. Furthermore, while identifying animals based on their sounds can provide valuable insights, gathering high-quality sound data can be time and resource-intensive, leading to limitations in sample sizes (Bravo Sanchez et al., 2021). In addition, observing animal behavior typically requires time and effort, often resulting in limited data and constraints on in-depth studies of specific behaviors (Arac et al., 2019). These circumstances give rise to imbalanced datasets and fewer samples from rare species for training neural networks (Høye et al., 2021).

Although the application of AI models in zoology has been slow compared to the broader biological sciences, the introduction of new technologies in specialized subfields often comes with an inherent time lag. To address these challenges, it is recommended to enhance data collection initiatives, focusing on long-term accumulation and integration with existing databases to mitigate data insufficiency. In situations of limited sample sizes, employing pre-training and transfer learning methods would be beneficial ((Høye et al., 2021; Vélez et al., 2022). For data concerning rare species or of low quality, applying data augmentation methods such as image manipulation and geometric transformations can expand training datasets (Klasen et al., 2022). Model-agnostic meta-learning (Shui et al., 2023) and multiset feature learning (Jing et al., 2021) could offer innovative solutions to these issues (Shui et al., 2023; Jing et al., 2021). When encountering species not present in existing databases, the challenge becomes even more significant. Addressing this situation necessitates the application of multiple class anomaly/novelty detection or open set/world recognition (Perera & Patel, 2019; Turkoz et al., 2020). Moreover, simpler models such as logistic regression, K-Nearest Neighbor Regression, and SVM may be more suitable in these cases. To address generalization issues, emphasis should be placed on data integrity through meticulous cleaning and quality control processes. Leveraging pre-trained models and fine-tuning them on specific tasks can also aid in adapting to varied species data (Lin et al., 2023). Lastly, the broader dissemination and implementation of these AI technologies should be encouraged, alongside fostering collaborative efforts between AI experts and domain specialists.

Supervised learning plays a pivotal role in zoological research due to its close association with species classification, behavior identification, and regression tasks in feeding behaviors. Supervised learning requires high-quality annotated data to train models and produce highly accurate predictions. As discussed in the “Animal Classification and Resource Protection” section, certain species classification models have shown suboptimal accuracy (Bravo Sanchez et al., 2021), which may be partly attributed to a lack of labeled data for supervised learning. To address this issue, techniques like semi-supervised, which combines supervised and unsupervised learning, and weakly supervised learning have been applied in the field of AI, offering potential methodologies for zoological research.

## PROSPECTS FOR FUTURE WORK

Deep learning models, particularly CNNs, are favored by researchers as predictive models due to their local receptive



fields and convolutional architecture, which make them effective at processing image data. However, their efficacy in handling sequential data, such as text and video recordings, is less satisfactory compared to linguistic models such as LSTM and BERT. The main limitation of CNNs is their inability to effectively capture and preserve the positional dependencies inherent in sequential data. Thus, zoological researchers may adopt different trajectories, which is not necessarily problematic but warrants further exploration. Supervised learning is also prevalent in zoological studies, commonly chosen for fitting models and performing classification tasks. In contrast, unsupervised learning is less frequently used, primarily for generative and clustering tasks, due to the absence of supervised labels. Reinforcement learning also draws inspiration from zoological studies exploring animal decision-making behavior derived from neuronal activation. Such integration is expected, as the field of zoological research emphasizes using AI models to address specific, domain-related challenges spanning supervised, unsupervised, and reinforcement learning.

The integration of AI into zoological research promises a paradigm shift, enhancing efficiency, accuracy, and scope (Wang et al., 2023a). AI will enhance data collection and interpretation by increasing efficiency, reducing time expenditure, and improving accuracy, especially in handling complex data like intricate sounds and high-resolution images (Shen et al., 2022b). AI will enable real-time, non-invasive monitoring of wildlife, in contrast to traditional methods that are often invasive and limited. AI technologies also promote objectivity in behavioral analysis by automating processes and providing quantitative metrics. The focus of zoological research is shifting from mere descriptive to predictive and explanatory models. This technology will also improve the verifiability and reproducibility of research, influencing the broader acceptance of theories. The interdisciplinary nature of AI also allows for the integration of computer science, statistics, and biology, facilitating the development of new theoretical frameworks. AI further democratizes zoological research by enabling public participation in data collection, such as through social media-based wildlife monitoring (Foglio et al., 2019). Paradigm shifts are not usually completed in the short term but are gradual, evolving transformations. However, as the application of AI in zoology becomes increasingly widespread, we anticipate a series of profound changes in this field, including in the evolution of theoretical frameworks. These changes will advance our understanding of the complexity of the animal world in a more comprehensive and in-depth manner.

In the future, beyond the establishment and use of cameras in nature reserves, AI will also be able to utilize satellite images, climate data, and drones to detect changes in animal populations or potential threats like poaching, helping to predict areas where endangered species can reproduce and thrive. The integration of AI with biological recording devices will also revolutionize the study of animal migration, behavior, and physiology under natural conditions. The potential development of a global platform will enable zoologists worldwide to collaborate, share data, and utilize AI tools collectively for analysis.

Zoological research can also directly influence model design, drawing insights from animal neuroscience and behavioral studies (Yu, 2016). Furthermore, the zoological domain provides a vast and diverse dataset, supporting

comparative analysis of models across different architectures and theoretical paradigms. As a result, it serves as an ideal experimental platform for AI models requiring extensive data resources. Therefore, the relationship is not just about applying AI to zoology but is mutually beneficial for both disciplines.

## CONCLUSIONS

This review comprehensively examines the integration of AI within zoological research, outlining the primary tasks, core models, datasets, and the challenges encountered in this field. AI algorithms have been instrumental in advancing various subfields, managing complex data forms, and achieving leading-edge predictive accuracy. The combination of AI and zoological research harnesses the computational power of “bytes” to successfully decipher the inner secrets of “beasts”. Given the increasing demand for analyzing data generated from laboratories, natural habitats, and agricultural settings—including but not limited to images, text, tables, videos, gene sequences, and molecular structures—the strategic selection and application of AI models tailored to specific scientific inquiries is expected to gain momentum.

## SUPPLEMENTARY DATA

Supplementary data to this article can be found online.

## COMPETING INTERESTS

The authors declare that they have no competing interests.

## AUTHORS' CONTRIBUTIONS

Y.J.Z. and Z.C. conceived the review. Y.J.Z., Y.S., J.L., Z.L., and Z.C. prepared the manuscript, figures, and tables. All authors read and approved the final version of the manuscript.

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