

# Innovations

## A Brief Review on Applications of AI in Herpetology

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**Abstract:** *Herpetology, the study of reptiles and amphibians, may seem to be a trivial field, but in truth, it is of the utmost importance to mankind. Artificial intelligence, when combined with herpetology, can do wonders by performing tasks that are near impossible for humans. However, herpetologists often lack technical knowledge of computer science, and vice versa. This article introduces basic concepts of artificial intelligence and summarizes existing applications of AI tools in herpetology. This allows scientists from both fields to have a preliminary understanding of the existing literature, which, in turn, facilitates developments of better tools in future.*

**Keywords:** *Herpetology, artificial intelligence, machine learning, deep learning, neural networks*

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### **Introduction**

Around 81,000 – 138,000 people annually succumb to snakebite as per the World Health Organization (WHO)<sup>[1,2]</sup>. Crocodile attacks have an imminent need for control too. A study in Tanzania found that as high as 58% crocodile attacks can be fatal to humans, with most victims comprising of children<sup>[3]</sup>. Salmonella infections associated with reptiles is also a known issue<sup>[4,5]</sup>. On the other hand, reptiles and amphibians (herpetofauna) can be quite beneficial as well. They act as natural pest control, reducing rodent and insect borne diseases<sup>[6]</sup>. Amphibians are also excellent bio-indicator species as they are often quick to react to environmental changes, giving us preliminary caution regarding things like pollution levels, climate changes etc<sup>[7,8]</sup>. Snake venom helps making live saving antivenom<sup>[9]</sup>. All of this, along with the severe loss of biodiversity recently makes

herpetology, the study of reptiles and amphibians to be an extremely important field of study<sup>[10]</sup>. Certain tasks associated with herpetology, such as identifying species, listening to recordings of amphibian calls etc. can be tedious and daunting when done manually. Other tasks like having to visually identify species that look the same can be almost impossible for a human.

Artificial intelligence and machine learning can automate things that are difficult for humans. Integrating these tools can therefore greatly enhance the abilities and efficiency of herpetological tasks. There have been quite a few studies proposing and comparing such methods. However, such published studies are mostly authored by computer experts which makes them difficult to grasp for traditional herpetologists or other zoological scientists<sup>[11]</sup>.

Applications of artificial intelligence and machine learning algorithms are becoming more and more common in various fields of science including herpetology<sup>[12]</sup>. Databases such as iNaturalist and India Biodiversity Portal act as excellent online resources to train machine learning models<sup>[13,14]</sup>. A foundational understanding of the technologies used is therefore, necessary for anyone involved. On the other hand, computer scientists would need a summary of the existing models and publications to improve and create efficient tools in the future. This paper addresses this by first providing a concise overview of the basic concepts in artificial intelligence and machine learning. It then summarises recent studies done on the applications and comparisons of artificial intelligence tools, models and algorithms in the field of herpetology.

## **Review of Literature**

### **Artificial Intelligence (AI)**

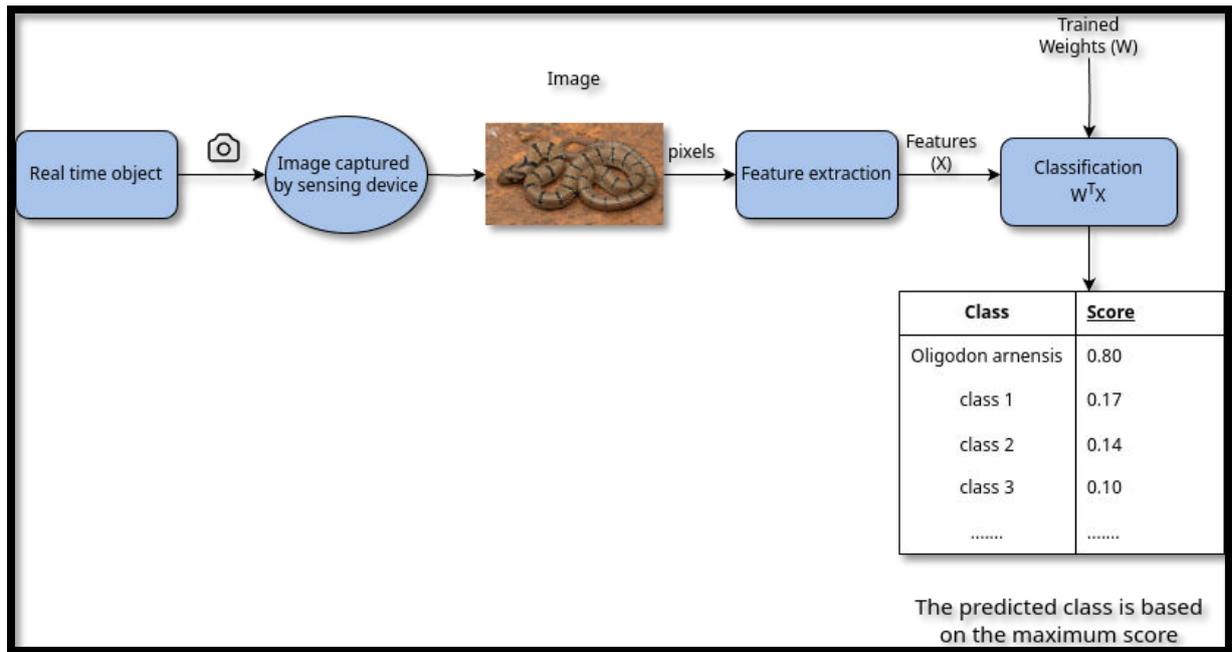
Artificial intelligence (AI) is the ability of computer systems to perform tasks that simulate human intelligence<sup>[15]</sup>. Although artificial intelligence is yet to catch up to the abilities of actual human intelligence, it is a rapidly evolving frontier. In the last couple of years, the field of AI has seen significant evolution and development. Alongside such rapid evolution, the application of AI in various fields of science is becoming increasingly impactful and common. Although there have been a few ramifications, such as widescale usage of generative AI in academic cheating, artificial intelligence overall has proven to be a very useful tool<sup>[12,16,17]</sup>. The Artificial Intelligence Index Report 2024, published by Stanford University, notes in detail how AI has been aiding scientific development, especially in recent years<sup>[12]</sup>.

### **Machine Learning**

Machine learning is a sub-discipline of artificial intelligence. In machine learning, computer systems learn from a given set of data (training), to be able to perform a task with a new set of data (inference). This way computer systems can accomplish tasks without being explicitly programmed for it<sup>[11,18,19]</sup>.

An overview of various training methods for machine learning algorithms is given below: -

- **Supervised learning**– In supervised learning, the computer is provided with a training dataset, where the data has already been tagged with the right answer/classification. This type of dataset is known as “labelled dataset”. The machine analyses the labelled dataset and associates features present in the data to their given labels. The algorithm can then be provided with a new dataset, which is not labelled and is unknown to the machine. Even though this new dataset is unknown to the machine, using what it has learnt from the training data, the machine learning algorithm should be able to predict the correct answer/classifications for the new dataset<sup>[20,21]</sup>.
- **Unsupervised learning**–In unsupervised learning, the computer is provided with a training dataset, where the dataset is not labelled or tagged like the training datasets of supervised learning algorithms. The machine would have to analyse the unstructured training data by itself to identify patterns, similarities or differences between the data and organise them, without receiving any guidance<sup>[22,23]</sup>.
- **Reinforcement learning**–Reinforcement learning follows a trial-error approach. Unlike, supervised learning, the machine does not receive a labelled dataset. Instead, after each action, it receives feedback in the form of rewards and penalties, on whether its action is correct, wrong or neutral<sup>[24,25]</sup>.
- **Semi-supervised learning**–Semi-supervised learning sits on a middle ground between supervised and unsupervised learning. In this method, a small part of the training dataset is labelled with the majority being unlabelled. When a large dataset is available but it’s too costly or challenging to label all of it, this approach can be useful<sup>[26,27]</sup>.



**Figure 1: A pipeline diagram for how a machine learning algorithm takes in an image and outputs confidence scores for various classes.**

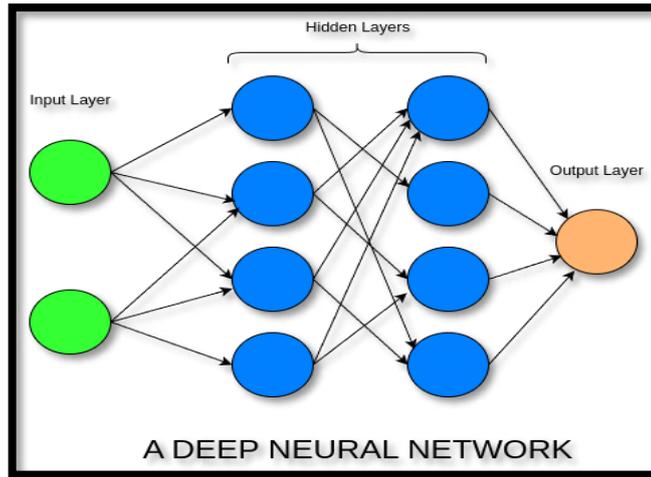
**Source: Diagram created by ShrishjayAcharya**

**Deep Learning**

Deep learning is a sub-discipline of machine learning. The concept of deep learning is meant to mimic the function of the human brain. Deep learning leverages deep neural networks with multiple layers (explained below). By using these layers, the deep learning model can recognize complex patterns in the given data. This enables the model to accurately perform tasks like visual object recognition and object detection<sup>[28,29]</sup>.

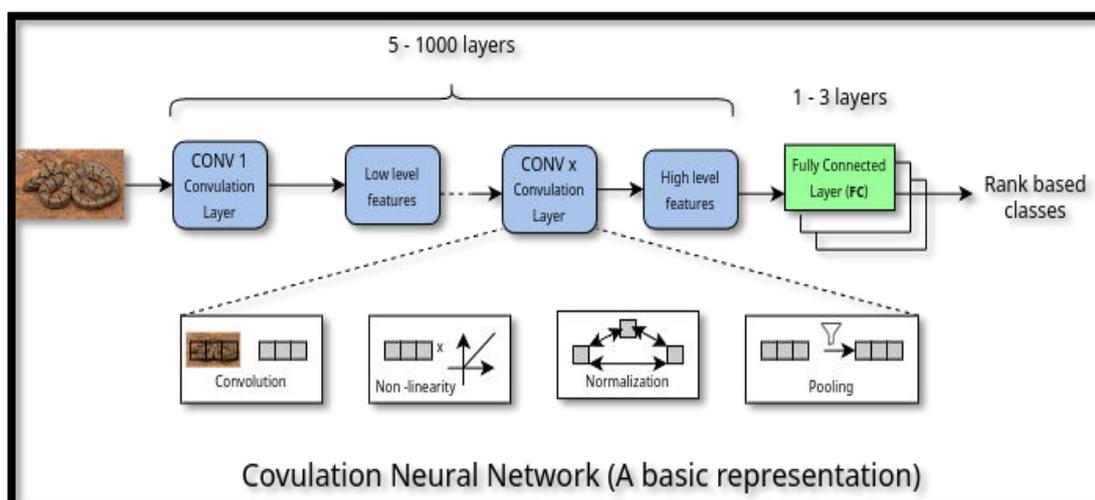
A few key terms related to deep learning: -

- **Deep Neural Networks** – Deep neural networks are machine learning models that can perform complex tasks like recognizing different objects, sounds etc. They excel when a large labelled data is provided. Deep neural networks also provide highly accurate results in voice and sound recognition. Larger datasets result in greater accuracy with these models<sup>[29]</sup>.



**Figure 2: Diagram of a deep neural network.**  
**Source –Diagram created by ShrishjayAcharya**

- **Real Time object detection** –Real-time object detection focuses on locating and identifying objects in a video stream or image sequence as it is captured in real time. This allows systems to analyse and respond to visual data instantaneously or with minimal delay, which is paramount to applications needing immediate decision-making and interaction. Various deep learning models are designed to detect objects in real time like CNN, YOLO<sup>[30,31]</sup>
- **CNN (Convolutional Neural Network)** –CNNs are a class of deep neural networks used for analysing data which has a grid-like structure. They are often used to process images and perform tasks like image recognition and classification<sup>[31]</sup>.



**Figure 3: A basic representation of the CNN architecture**  
**Source: Created by ShrishjayAcharya**

- **YOLO (You Only Look Once)** –YOLO (You Only Look Once) is a popular algorithm used for real-time object detection. That means, YOLO is designed for quickly detecting objects within an image. Unlike other conventional object detection systems, YOLO analyses the image in one go rather than analysing it multiple times. This allows YOLO to yield fast results while still being accurate<sup>[30]</sup>.

### **Herpetology**

Zoology is a branch of science devoted to the study of animals (Kingdom Animalia)<sup>[32]</sup>. Herpetology is a branch of zoology, specifically focusing on reptiles and amphibians. This field encompasses the biology, taxonomy, ecology, husbandry, behaviour of reptiles and amphibians such as snakes, lizards, frogs, toads, turtles, salamanders, newts, tortoises, crocodylians etc<sup>[33]</sup>. Herpetology does not include the study of birds, even though birds are considered to be reptiles today<sup>[34,35]</sup>. Instead, zoology has a separate branch devoted to the study of birds, called Ornithology<sup>[36]</sup>.



**Figure 4: Herpetology is the study of reptiles and amphibians. Left – Ananimalai spiny lizard (*Saleaanamallayana*); Top Right – Bamboo pit viper (*Craspedocephalusgramineus*); Bottom Right – Kodaikanal bush frog (*Raorchestesdubois*)**

**Source – Photographed by Avrajjal Ghosh**

### **How Artificial Intelligence is Used in Herpetology**

The ways artificial intelligence has been applied in the field of herpetology so far are discussed below: -

- Image analysis for snake species identification** – Identifying a snake by just looking at it is not always a reliable method of identification for a herpetologist. Methods such as looking at scalation patterns, morphological features, scale counting, identification keys or even taking the geographical location into account are often used<sup>[37]</sup>. Molecular data is used often in herpetology and sometimes, it can be impossible to identify two species separately without using molecular data<sup>[38,39]</sup>. Such precision is necessary to avoid errors in important research works involving taxonomy, systematics, molecular phylogeny, conservative efforts etc. However, for educating layman such complexity is unnecessary. People often get confused amongst similar looking snakes, such as mistaking a non-venomous snake for a venomous one (figure 5). This gives rise to fear, anxiety which can lead to unnecessary slaughtering of the harmless snake<sup>[37]</sup>. Machine learning algorithms can identify wildlife from images<sup>[40]</sup>. A deep learning model intended to help park rangers/tourists, attempted to identify 9 snake species found in the Galápagos Islands, by analysing photographs of snakes. The model uses R-CNN architectures and reached a holistic accuracy of 75%<sup>[41]</sup>. Another study targeting 6 species of snakes found in Iran's Lar National Park, found MobileNetV2 to be very useful in identifying snake species. The study also stated that this technology can be used on a mobile device, which can be the first milestone towards developing mobile applications of this kind<sup>[42]</sup>. Another model used a YOLO algorithm to identify snake species from images<sup>[43]</sup>. A different study, which developed an algorithm for identifying snake species from images even tested their software's effectiveness against human experts<sup>[44]</sup>.



**Figure 5: Common wolf snake (right) and common krait (left), two species that are often misidentified by common people.**

**Source – Photographed by Arghyadip Roy in Southern West Bengal, India.**

- **Image analysis for cryptic species identification** – The term “cryptic species” refers to species that are difficult to visually or morphologically identify. A study used deep learning to identify cryptic species belonging to a species complex of wall lizards (*Podarcishispanicus*) by using photographs of wall lizards. While humans face difficulty in visually identifying species with similar morphological characteristics, results of the study suggest deep learning to be quite accurate in the same task<sup>[45]</sup>.
- **Analysis of bioacoustics recordings** – Bioacoustics is a discipline of science that studies the production, transmission and reception of sounds made by animals<sup>[46]</sup>. Bioacoustics is used often in herpetology, especially in Anura groups (toads, frogs)<sup>[47,48]</sup>. Manually analysing gigabytes of recordings is extremely time consuming, which calls for automating the process<sup>[49]</sup>. Machine learning models have helped sort through acoustic recordings of frog callings and even classify them into different species based on those recordings. These types of analysis can then help in things such as estimating species richness, biodiversity monitoring, analysis of reproductive phenology, or even identify undescribed species<sup>[50–54]</sup>.
- **Analysis of geometric morphometric data** – A study conducted using supervised machine learning methods found plastron (bottom shell of turtles) shapes to be an effective way of distinguishing turtles belonging to the family Emydidae. However, the same methods seemed quite unsuccessful in distinguishing two cryptic species of turtles named *A. pallida* and *A. marmorata*<sup>[55]</sup>. Another machine learning model used morphometric data to identify sex of Asian water monitors (*Varanussalvator*) (Figure 6).<sup>[56]</sup>



**Figure 6: A juvenile Asian water monitor (*Varanussalvator*)**  
**Source – Photographed by Avrajjal Ghosh in Kolkata, India in 2012**

- **Species Distribution Modelling (SDM) with machine learning** – Species distribution modelling (SDM) refers to creating models to estimate distribution of a species, by employing computer algorithms. The SDM models use environmental data to forecast the distribution of a species across geographical locations and over time<sup>[57]</sup>. Machine learning can also be used in SDM. For example, a study used Maxent, which is a type of machine learning SDM to create a distribution model of the Jemez Mountains salamander (*Plethodon neomexicanus*)<sup>[58]</sup>.
- **Predicting structure of snake venom proteins** – Biological functions of a protein is intricately related to its structural configuration. Tools like AlphaFold2 (AF2), ColabFold (CF) and MODELLER (MDLR) have been used to study the structural configuration of snake venom proteins. However, their sensitivity and accuracy in deciphering complex proteins in snake venoms have shown concerning inconsistency. When dealing with proteins that lack experimental structure and evaluation is done using Clash score, MolProbity score as well as Ramchandran score, non-homology based approaches like AF2 and CF exhibited superior performance in all evaluated parameters, when compared to homology-based model like MODELLER. Thus, availability and easy accessibility of powerful computation tools can be a game changer in the field of structural biology with wide spread implications<sup>[59]</sup>.
- **Predicting physiological condition of snakes using parameters of blood biochemistry** – Blood Chemistry of an organism reflects the physical and chemical changes in an organism, indicating general metabolic and physiological status. However, no haematological benchmark levels for different components of serpentine blood have yet been established. Till date classic statistical methods have played a pivotal role in analysing different blood parameters. However, approaches based on machine learning are gaining ground as they provide better classification models and greater insight into data. Machine learning methods don't make prior assumptions which eliminates bias and its inherent ability to uncover complex patterns is used to analyse sets of information from different biological sources. According to a study done on captive Balkan whip snakes (*Hierophis gemonensis*), serpentine blood parameters like Urea, Glucose and LDH can discriminate between different physiological states during the biological cycle of a snake thus helping in studying different snake behaviors<sup>[60]</sup>.

## **Conclusion**

AI has been making impactful contributions in various scientific fields over recent years. Studies conducted so far suggests that combining artificial intelligence with herpetology can be promising. AI can automate manual tasks like analysing bioacoustics and educate people about snakes by providing automatic snake

identification with decent accuracy. It can accomplish tasks impossible for humans, like differentiating between cryptic species visually. It can even offer some novel approaches such as predicting protein structures, predicting physiological condition of a snake by analysing its biochemistry parameters, distribution modelling and analysis of morphological features of herpetofauna. On the other hand, some of the tasks such as identifying species with extreme precision is currently almost impossible to be automated with artificial intelligence and must be done manually. Overall, artificial intelligence shows extreme potential in the field of herpetology when used wisely.

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