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A review of using deep learning from an ecology perspective to address climate change and air pollution

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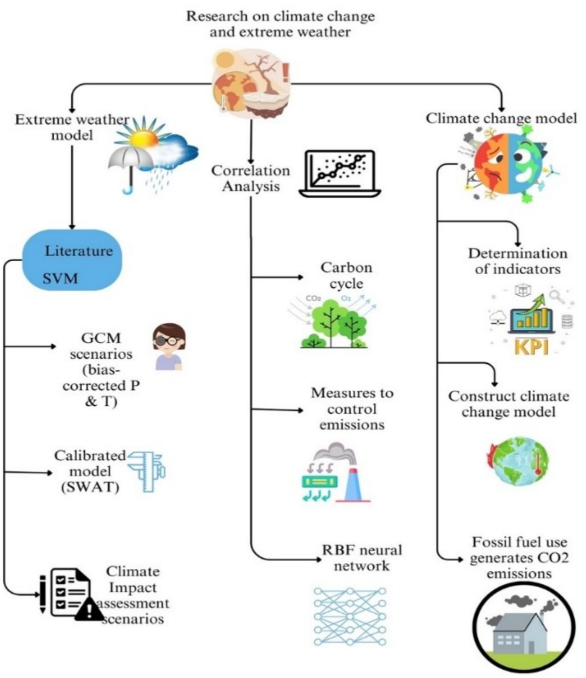
Graphical abstract



Abstract

Deep learning, a unique class of artificial intelligence techniques that can shatter pattern recognition accuracy records, has recently attracted a lot of attention. With its flexibility and capacity to handle massive and complicated datasets, deep learning has transformed numerous academic domains, including bioinformatics and medicine, in a few of years. We think ecologists can also benefit from these methods, since ecological datasets are getting bigger and more complicated. This review examined current implementations and demonstrates how deep learning has been effectively applied to classify animal activity, identify species, and estimate biodiversity in big datasets such as audio recordings, videos, and camera-trap photos. This review paper show that most ecological disciplines, including applied contexts like management and conservation, can benefit from deep learning. This review also identify frequent problems concerning the application of deep learning, like what is the process for building a deep learning network, what resources are available, and what kind of data and processing power are needed. One of the biggest problems confronting humanity is climate change, and as deep learning (DL) specialists, you might be wondering how we can help. Here, we go over how machine learning (ML) can be an effective tool for cutting greenhouse gas emissions and assisting society in adjusting to a changing environment. We collaborate with various sectors to discover critical issues, such as disaster prevention and smart grids, where DL can bridge current gaps. This paper provides a thorough investigation of modelling using deep learning networks on actual air pollution data. With the support of this research, we hope to create deep learning air pollution structures in the future and improve the outcomes even more with knowledge from recent developments in deep learning research, including Generative Adversarial Networks (GANs), which pit two rival networks against one another to produce accurate data and forecast the state.

Keywords: Climate change, environment, deep learning, management, air pollution, bioinformatics

1. Introduction

Evolutionary biology and ecology study intricate relationships and processes. Because of this, basic concepts like heredity, natural selection, adaptation, population dynamics, and food webs have to be understood and explained using a mathematical toolbox in order to understand organic evolution and ecological interactions. Mechanistic modelling of growing complexity nowadays enables us to do a variety of tasks, such as assembling and sequencing genomes, identifying features under selection, modelling the processes of extinction and adaptation, and evaluating animal populations. In addition to genetic sequences, the deluge of data that modern biologists deal with also includes digital information about samples, animals, and species. The creation of analytical tools that can offer fresh perspectives, increased effectiveness, and user-friendliness is being fueled by this abundance of data (Christin, S *et al.* 2019). The growing body of data provides previously unattainable insights, but it also complicates several elements of ecological and evolutionary inference in real-world applications.

Complex models are frequently better suited to describe complex patterns, and researchers must create each new model. Furthermore, mechanistic methods that take into account a large number of variables could be so computationally expensive that they can no longer be used with the kind of data that is regularly created in contemporary research (Rammer, W. and Seidl, R. 2019). Machine learning is a viable substitute. Finding a model that does well at generating predictions from the data is the aim of machine learning. In comparison, data modelling techniques presume that the model producing the data is already known. In its broadest sense, machine learning has been used for decades to optimise many model-based inference processes in ecology and evolution, such as Markov chains and genetic algorithms (Borowiec, M. L. *et al.* 2022). It is also used for data transformations and clustering, such as principal component and discriminant function analysis, K-means. With a plethora of novel algorithms and applications, machine learning has witnessed a sharp increase in popularity in recent times.

One method that is quickly gaining traction is deep learning. Artificial neural networks, or ANNs, are multilayered, networked processing units that are essential to deep learning. The last ten years have seen a sharp increase in the popularity of neural networks due to advancements in hardware, high-level software democratisation, and algorithmic innovations. Emerging technologies like self-driving cars rely on deep learning, which has also significantly improved commonly used IT products like speech and picture recognition and automatic language translation. One of the main advantages of deep learning over other machine learning techniques is that it made these results possible. Important data features must frequently be first found using expert domain knowledge in classical machine learning (Capinha, C, *et al.* 2021). This is a drawback in cases like photos where characteristics that accurately describe the data are not readily apparent or are challenging to extract. Deep neural networks get around this by automatically identifying the most significant patterns and features in the data. Deep learning is currently being used by researchers to solve a variety of ecological and evolutionary biology-related issues, including population genetics, phylogenetic inference, environmental monitoring, community science initiatives, and sequencing equipment output processing. This review defines neural networks, describe their operation, list the ecological and evolutionary biology challenges to which they have been used, and outline the advantages and disadvantages of neural networks.

In a short period of time, deep learning, a subfield of machine learning, has impacted many scientific fields and daily activities. Because of this artificial intelligence discipline's great performance and versatility, it has grown in popularity. After breaking accuracy records in speech recognition and image classification, deep learning algorithms gained popularity. Since then, this technology has grown quickly, completely changing the way we utilise computers to automatically identify particular features in data and carry out operations like prediction, clustering, and classification (Ditria, E. M *et al.* 2020). These instruments are presently being used in a wide range of scientific and technological domains, including bioinformatics and medicine. A new breed of data-driven computational tools has emerged as a result of the rapid advancements in hardware and software, as well as investments from the public and commercial sectors. Deep learning, a type of machine learning methods that employs DL to find patterns in big, diverse datasets, has received a lot of attention lately. Ecologists and others have reacted to these findings with both excitement and doubt. The background of deep learning techniques, the deep learning techniques most pertinent to ecosystem ecologists, and some of the challenging domains they are used in are all covered in this paper. Deep learning techniques make use of the vast amounts of data that are currently accessible and exhibit excellent predictive achievement in a variety of ecological scenarios. Moreover, ecosystem ecologists now have new avenues for learning about ecosystem dynamics thanks to deep learning methods. A link between causal explanation and pure prediction is made possible, in particular, by recent developments in interpretable ML and the creation of hybrid techniques fusing DL with mechanistic models.

Taking into account the intricacy of ecological data and the continuously expanding magnitude of ecological datasets—a fact that has been exacerbated recently by the widespread usage of automatic recorders. We think that for many ecologists, deep learning can be an essential tool. In fact, over the past 20 years, various machine learning techniques have been successfully applied and documented in the field of ecology. These techniques include artificial neural networks, genetic algorithms, support vector machines, and random forests. To our current knowledge, nevertheless, there isn't a comprehensive summary of the situations in which ecologists would find deep learning to be helpful.

AI has the power to completely change how we investigate and comprehend the natural world. AI can be used in ecology in a variety of ways, including as the analysis of sizable datasets, the creation of prediction models, and the detection of trends and patterns in environmental data. Artificial intelligence is already being used by ecologists, including Han, to find patterns in massive data sets and improve the accuracy of forecasts. Examples of these predictions include whether novel viruses have the potential to infect people and which animals are most likely to carry them. The current study contends that there are numerous further opportunities to use AI in ecology, including the synthesis of large data and the identification of weak points in intricate systems. The authors contend that more resilient and flexible AI architectures may be inspired by the extraordinary durability of ecological systems. Specifically, ecologists claimed that understanding ecology could aid in resolving the issue of mode collapse in artificial neural networks—the AI systems that frequently underpin computer vision, speech recognition, and other applications.

This paper demonstrates how deep learning's adaptability can benefit the majority of ecological disciplines, even in practical settings like management and conservation. We list typical problems and offer solutions and materials to assist ecologists in determining whether deep learning is a suitable analysis technique for their research.

2. Deep learning functions

We first outline the common origins of deep learning and machine learning in order to summarise it. All things considered, machine learning is a class of algorithms that can automatically produce prediction models through the identification of patterns in data. Because they can evaluate complex nonlinear data with interactions and missing data—which are common in ecology—these methods are of interest to ecologists (Pichler, M. and Hartig, F. 2023). Ecology has previously benefited from the successful application of machine learning for tasks including animal behaviour research , ecological modelling, and categorization. The ability of deep learning algorithms to extract features from data is what sets them apart and gives them their immense strength. First, computers are capable of autonomously learning from unlabeled data, automatically finding patterns and similarities.

This approach, which has no set result expected, is frequently used as an exploratory tool to find patterns in data, shrink its size, or group together related data sets. Second, training under supervision is another method of learning. Initially, the computers are given a tagged dataset containing the target items so they may learn to correlate the labels with the samples. Then, using different datasets, they are able to detect and identify these items (Christin, S *et al.* 2021). However, just providing the labels is not enough in traditional machine learning. Additionally, the user must tell the algorithm what to search for. For example, in order for the algorithm to identify giraffes in photos, it has to know the precise characteristics of the animals—such as their size, colour, form, and patterning—expressed in terms of pixel patterns. This might be a challenge to non-machine learning experts as it typically necessitates a thorough understanding of the system under study and proficient programming abilities.

Deep learning techniques, however, omit this stage. Deep learning systems can automatically identify and extract characteristics from data using general learning techniques. This implies that, given enough samples, a deep learning system can be trained to recognise giraffes on its own; all we have to do is inform it whether a giraffe is present in a given image (Alshahrani, H. M.etal 2021). By breaking down the data into several layers, each with a different level of abstraction, the algorithm is able to learn complicated features that represent the data, enabling such an automatic learning process. The rapid rise and widespread use of deep learning techniques can be attributed to their great predicted accuracy in auto-identifying features in complicated, high-dimensional data. Furthermore, deep learning is particularly precise and effective when it uses highly dimensional datasets that are typically provided by ecology studies conducted at a variety of scales, from the individual to the metaecosystem. Since there are various deep learning architectures accessible, there are several approaches to actually accomplish these findings in practice. Convolutional neural networks (CNNs) are the most prominent among them; their effectiveness in picture classification contributed to the rise in popularity of deep learning.

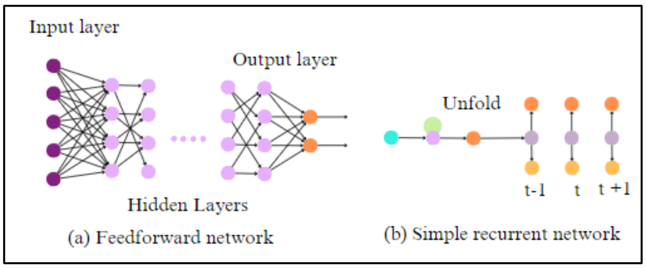


Figure 1. Common deep neural network architecture.

3. Various designs for deep neural networks

Deep learning algorithms are, technically speaking, multilayered neural networks. Neural networks are models that process information in a manner reminiscent of biological processes. Neural units, or highly interconnected processing units, collaborate to solve issues (Figure 1). The three major components of a neural network are the processing core, which houses one or more hidden layers, the input layer, which receives the data, and the output layer, which outputs the model's result (Willi, M, *et al.* 2019). The number of hidden layers, which indicates the network's depth, is what sets a deep neural network apart from a regular neural network. Regretfully, opinions regarding the number of hidden layers needed to distinguish between shallow and deep neural networks are divided.

The network modifies its behaviour during training to provide the intended result. This is accomplished by comparing the model's output to the right response in order to compute an error function. The network then makes an effort to minimise it by modifying the weights, or internal parameters of the function, usually through the use of a technique known as gradient descent. Deep networks contain a variety of structures. Feedforward networks use a fixed number of layers to map an input of a given size to an output of a defined size (Fairbrass, A. J. *et al.* 2019). The CNN is one of the feedforward methods that has drawn the most interest because of its strong generalisation and ease of training. CNNs are based on biological visual systems and are intended to analyse large amounts of data, including colour images. Typically, they are composed of pooling layers and stacking groups of convolutional layers.

With minimal human intervention, computers can make intelligent judgements thanks to neural networks. This is due to their capacity to learn and model complicated, nonlinear correlations between output and input data. They are capable of the following duties, for example. Neural network architecture draws influence from the structure of the human brain. Neurons in the human brain communicate electrically with one another to form a sophisticated, highly interconnected network that aids in information processing. In a similar vein, artificial neurons comprise an artificial neural network, which collaborates to solve an issue. AI are software programmes or algorithms that, at their heart, use computing systems to complete mathematical computations. Artificial neurons are software modules, also known as nodes. There are several uses for AI. Image recognition is among neural networks' most often used applications. In order to identify objects in a picture, neural networks can be taught to detect particular features in the image, such as forms, edges, and colours. Despite differences in language, accent, tone, pitch, and speech patterns, neural networks are capable of analysing human voice. Speech recognition is used by virtual assistants such as Amazon Alexa and automatic transcription software to do duties such as these: Help contact centre representatives and categorise calls automatically Real-time conversion of therapeutic interactions into documentation; precise subtitling of films and meeting recordings for a larger audience

Recurrent neural networks (RNNs), on the other hand, typically only have one hidden layer and process items one at a time while remembering previous elements and using each output as an input for the subsequent element. Thus, the sum of all the individual steps can be viewed as a single, extremely deep feedforward network. According to (Miao, Z.*et al.* 2019), this makes them especially intriguing for sequential input like voice or time series. The Long-Term Short-Memory network is a widely used RNN implementation that can learn long-term dependencies and has shown to be particularly effective for jobs like speech recognition.

4. How do neural networks learn? What are they?

Artificial neural networks and their use as tools for inference can be defined in a number of ways. While there are limitations to the most obvious biological analogy, it is useful to think of neural networks as brain-inspired computer algorithms (Schneider, S. *et al.* 2019). They are made up of interconnected layers of nodes, or "neurons," and connections, or "synapses," that can learn by varying the strength of their connections and how easily they fire. Neural networks can be utilised with almost any input that can be represented numerically since computers represent these layers and connections as matrices of numbers that can be manipulated by linear algebra operations (Lamba, A. *et al.* 2019). Neural networks are mathematically just a function that maps input onto a desired output.

Despite their general simplicity, neural networks are incredibly powerful because of this design: a feedforward network, which is a network with information flowing from input to output layer with at least one intermediate layer, can approximate any continuous function, no matter how complex. For example, these approximations can describe individual pixels in an image. Deep neural networks, on the other hand, are networks with numerous intermediary layers that can learn to recognise high-level ideas like lines, geometric structures, and even entire sceneries (Torney, C. J. et.al 2019). While ANNs are trained on nonlinear functions, their output can be either continuous numbers or the certainty that the input is part of a particular data class. However, as point out, this confidence does not always equate to the frequentist likelihood that the forecast is correct (Graving, J. M. *et al.* 2019). Such networks can thus be used to develop classifiers, which are models differentiating among discrete categories, as well as regression models, which infer continuous values. The majority of ANN applications depend on the network's ability to learn and generalise to new input, which is not possible with feedforward operations alone.

An ANN must be able to evaluate the accuracy of its predictions and modify its parameters to enhance its performance in order to be considered a predictive tool. A loss function is a way to quantify how far off the network's output is. Cross-entropy, or logistic loss, is one type of loss function (Borowicz,*et al.* A. 2019). When the aim is to classify inputs into discrete, pre-defined classes, cross-entropy (CE) is employed. A method for determining the combination of parameters that minimises the loss function is also required by the network. To determine how parameters contributed to the loss (error), it is necessary to trace the error back across the network once it has been measured at the output. This procedure, known as backpropagation, finds the gradient of the loss function with respect to the trainable parameters of the network using chain rule calculus. Gradient descent is the procedure of raising or lowering parameters so as to minimise the derivative of the loss function (Cui, S., *et al.* 2023). The goal is to identify the set of weights and biases that produces the least amount of loss or mistake. Since no such learning mechanisms are known to exist in biological neural systems, gradient descent and backpropagation show the limitations of the biological comparison. The training loop is the term for this repeated process that takes place each time a batch of training data is handled. When well designed, it enhances inference.

5. Convolutions network

An input tensor is transformed into an output known as a feature map using an action known as a convolution. It can be seen as a window (also known as a filter or kernel) that gradually moves across the input (see picture). A feature map is produced at each stage of a convolution by taking the dot product of the values in the input sector and those in the filter. The values in the filter are ones that the network can learn automatically (Stowell, D *et al.* 2019). For clarity, the bias term and activation function are not included in the feature map calculations, and filter values in the figure correspond to network weights. Because feature maps record information about the placement of specific visual cues, such as horizontal, angled, or vertical ones, they are essential in visual recognition tasks. "Feature extraction" is a common term used to describe the process of using a filter to identify data features.

For instance, the filter shown in the picture will create feature maps with diagonal edges "extracted" since it is sensitive to diagonal lines. In feature maps, input dimensions can be preserved by adding padding around the input. Networks frequently use many stacked convolutional layers, with each layer typically containing numerous filters and matching feature maps (Weinstein, B. G. et.al 2019). Then, sometimes after going through a pooling and/or dropout layer, feature maps from the preceding layer are used as input for the subsequent layer. Capturing intricate, hierarchical patterns is one area in which convolutional neural networks thrive. Figure 2 shows the network model. Although convolutions can be used with data of varying numbers of dimensions, they are often carried out in two dimensions, as in the example in the figure. One-dimensional convolutions, for instance, can be applied to text strings or time series data, whereas three-dimensional convolutions can be utilised with videos or three-dimensional images.

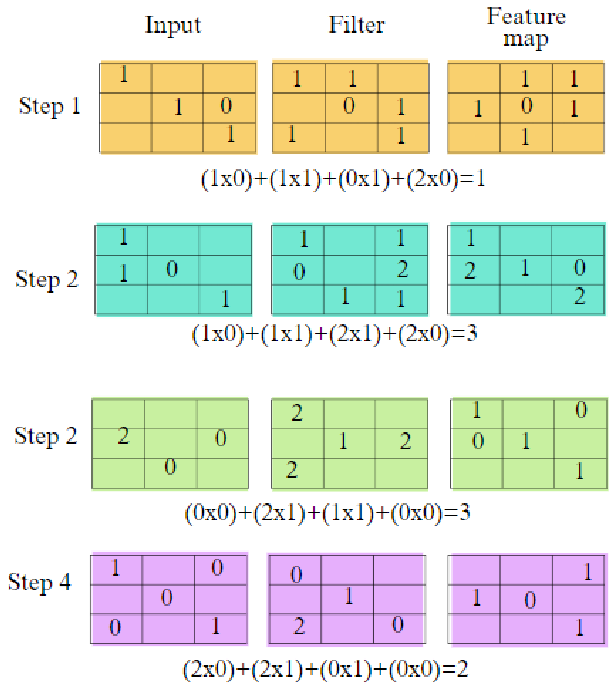


Figure 2. Network model

6. Dense network

Prior to training, input data in dense networks are often scrambled, and no information is retained between training batches (Goodwin, M., *et al.* 2022) As a result, correlations between successive data points are broken, making it impossible to forecast events using time-series data. This problem is addressed by recurrent neural networks (RNNs; panel B), which incorporate loops into their information flow. Information goes from the input to the output of the network, but it can also flow backwards from the output to the input of the hidden layer through recurrent weights (Wrec in panel B). This is how a simple RNN is conceptualised: it is a network with a single input, hidden layer, and output layer (Høye, T. T. et.al 2021). By joining neurons in the hidden layer over time, one may "unroll" the network and see how this process is carried out. Both representations are seen in the figure. However, because weights in these networks can diverge rapidly during training, basic RNNs like the one in the image are challenging to train. This issue is addressed by more sophisticated variations on the original RNN design, such as Long Short-Term Memory networks (LSTMs) and Gated Recurrent Units (GRUs), which are frequently employed with time-series data or in language processing applications. Recombination landscapes have been predicted in evolutionary biology through the application of deep learning methods, such as GRU.

Another neural network architecture is the variational autoencoder (VAE; figure panel C), which consists of two components: the encoder, which maps input data onto a predetermined number of latent variables, and the decoder, which reconstructs the original input (Benkendorf, D. J. and Hawkins, C. P. 2020). Most importantly, the encoder generates two vectors—one representing the mean and the other the standard deviation—for every latent variable. This results in the latent variables having a continuous space. VAEs have the ability to create new data instances that resemble the input yet differ from it. Using genetic data as input, population structure visualisation in two dimensions is one use of VAE. Similar to main components analysis in that they reduce data into a small number of useful dimensions, VAEs are also capable of nonlinear dimensionality reduction.

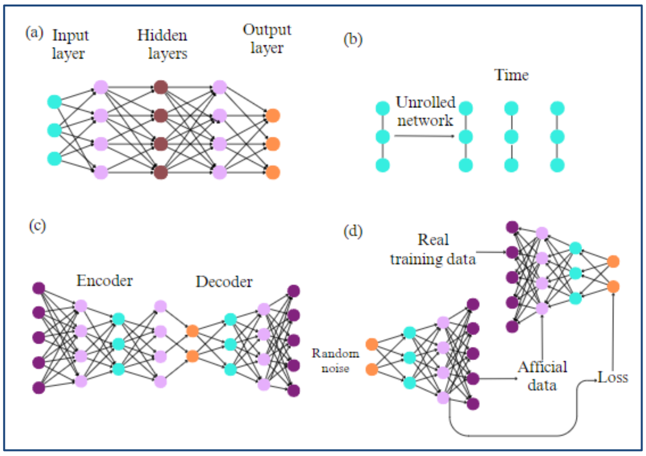


Figure 3. Dense network

A particular kind of neural network called a generative adversarial network (GAN; figure panel D) creates generated data through the interplay of two parts: a generator and a discriminator (Safonova, A et.al 2019). The generator generates false data that is believable and resembles samples from training sets. The input is categorised by the discriminator as either fictional or actual data. The generator translates random noise onto the artificial output, which can be fed into the discriminator together with actual training instances (Jo, T., Nho, K. and Saykin, A. J. 2019). The generator can be a variational autoencoder. While the generator is taught using information from the loss function computed on artificially generated examples, the decoder is trained to become more adept at differentiating between genuine and artificially generated examples. Figure 3 shows the dense network. In this manner, the discriminator and generator enhance each other's performance to generate data that is similar to input from the actual world. The creation of artificial genomic sequences is one application of GAN technology.

7. Overview of ecology applications

This reviewed articles that explain approaches that may be utilised in ecological studies, including behavioural detection or animal or plant identification, or that use deep learning techniques for ecological studies in order to determine areas where ecologists could benefit from using deep learning (Kahl, S. et.al 2021). The uses of deep learning in the biological sciences are outlined below. Understanding the distribution of both abiotic and biotic components of living things in the environment is the primary goal of ecology. The living and non-living elements as well as how they interact with the environment are referred to as biotic and abiotic variables. Our natural environment is greatly impacted by technology, from the biological waste produced by machines and their parts to the energy used by data centres. But the effects of technology go beyond these apparent outcomes and are evident in the way that entire ecosystems are changing. Not to be overlooked is the fact that technology may also benefit the environment by increasing energy efficiency, using renewable energy sources, and developing creative ways to manage resources sustainably.

This expanded the supplemental table by include pertinent references quoting that review in addition to reviews in order to conduct a representative literature evaluation. Each study article was categorised as follows based on the information gathered, neural network design, and application. The data that were gathered were categorised as follows: (a) images if the raw data included visible light images, even if the images were automatically processed before analysis (apart from manual measurements); (b) video if the original input consisted of moving images, even if the images were processed as individual frames; (c) sound, such as sonar, infrared, and ultrasound, even when examined as spectrogram images (Moniruzzaman, M. *et al.* 2019), (d) molecular information gathered as gene expression patterns, SNPs and allele frequency spectra, DNA, RNA, or protein sequences, (e) Time-series data of different formats; (f) environmental data, such as the physical or biological characteristics of the environment, species community composition and presence/absence; (g) other data, such as body measurements; and (h) other data, such as chromatography, sonar, LiDAR, and other remote sensing techniques.

The following primary categories of neural network topologies were identified by us: generative adversarial networks (GANs), variational autoencoders (VAEs), recurrent neural networks (RNN), convolutional neural networks (CNNs), variational neural networks (DNNs), including self-organizing maps, and other neural networks, including transformers. Application areas included (Kasabov, N. & K.*et al.* 2019): (a) classification, which is defined as the inference of discrete variables; (b) regression; (c) modelling or simulation of data or processes; (d) modelling of interactions; (e) segmentation of images; and (e) unsupervised clustering. Regression involves the inference of continuous variables or future events, object detection and counting; and scene understanding.

8. Classifications

Systems for automating the environmental monitoring of aquatic macroinvertebrates are also being developed, and camera trap systems and deep learning classifiers are already being employed for monitoring vertebrate animals (Wang, H. *et al.* 2019). Deep learning has also been used to identify objects using sonar data and audio recordings, including bat and bird sounds and even mosquito wingbeats. Figure 4 shows the overview of the various ecological applications of deep learning based on the study scale. It should come as no surprise that the technology has been used most frequently to identify species and track their abundance in bird calls. In most of these experiments, CNNs are trained on audio that has been transformed to spectrograms—image representations of sound—for use in visual identification tasks.

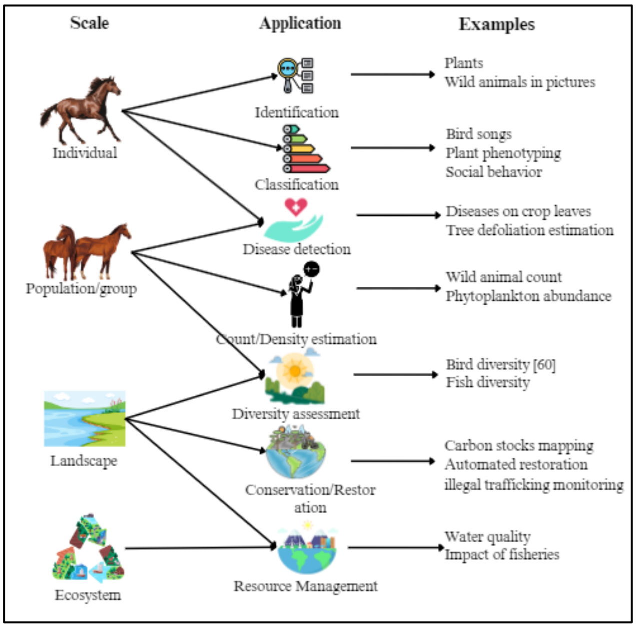


Figure 4. An overview of the various ecological applications of deep learning based on the study scale.

For the benefit of taxonomists, they can even collaborate with digital photographs of herbaria. These have evaluated the use of deep learning in image-based identification applications, for further information on the topic (Guo, Q, et.al 2020). Acoustic data such as bird songs, marine mammal vocalisations, and mosquito noises can also be utilised with deep learning. Additional uses include phenotyping, which is the classification of a species' outward traits in order to correlate them with its genotype (Sun, Y. *et al.* 2019). Examples of this include counting leaves to gauge a plant's growth or observing plant root systems to learn about their growth and interactions with the soil.

9. Studies on behaviour

Deep neural networks are useful for ethological research because they can automate the description of animal behaviour. For example, describing a person's body position and following their gaze can provide insight into their social behaviour. Camera trapping images have proven to be an effective tool for classifying and describing the actions of wild animals, such as eating and sleeping (Spiesman, B. J., *et al.* 2021). CNNs can even be used to locate and identify marked individuals in order to study the collective behaviour and social interactions of species like bees. This opens the door to powerful capture-mark-recapture approaches that can be used to a wide range of species. With telemetry records expanding daily, deep learning can identify patterns of activity like foraging. A research team has learned to predict diving activities from GPS data alone by training a CNN with GPS localizations along with time-depth recorder data used to detect seabird diving behaviour (Wu, C *et al.* 2019). Additionally, animal behaviour models can be made. For instance, an RNN was able to produce lifelike simulations of worm behaviour by evaluating footage of Caenorhabditis elegans, nematode worms. Its model served as a categorization tool as well. Additionally, theoretical models of the evolution of species recognition in sympatric species and courtship rituals in monogamous species have been developed.

10. Population monitoring

Such techniques can be scaled up to assist with population monitoring, as deep learning is used to recognise, identify, and classify persons in automatic monitoring data. For example, counting persons can be used to determine population size. As a result, since traditional methods have already been used to calculate information like population density and distribution, this data can likewise be used for those purposes (Middel, A, *et al.* 2019). Deep learning has a lot of promise for diagnosing illness symptoms, which is similar to the applications that are now used in fields like medicine. CNNs have been used, for example, to identify crop illnesses or tree defoliation. This method might be extensively used to search for signs of scarring, malnourishment, or the presence of in natural populations of plants and animals.

11. Modelling ecologically

For the purpose of forecasting in a world that is evolving gradually or for a deeper understanding of complicated processes, ecologists frequently need strong and precise predictive models. Deep learning techniques are just one type of machine learning approach that has demonstrated significant promise in this area (Guirado, E.*et al.* 2019). Recently, based on a species' ecological interactions with other species, a deep neural network has been able to accurately generate distribution models of those species. When sufficient data are available, these techniques may also be used to explore ecological interactions (Banerjee, A. et.al 2019). Though they haven't been used in this manner yet, deep networks have the ability to simulate how environmental factors affect living things. Research in the medical domain was able to forecast human gastrointestinal morbidity. For phytoplankton and benthic communities, recurrent networks have also been demonstrated to be effective in predicting abundance and community dynamics depending on environmental variables (Chen, Z. *et al.* 2021). Overall, research suggests that deep learning may find its way into the ecological niche modelling toolkit due to its considerable potential for forecasting species distribution based on environmental parameters.

12. Conservation and management of ecosystems

Since all ecosystems are impacted by human activity, ecologists' primary responsibility is to observe, analyse, and comprehend these ecosystems' changes for the sake of management and conservation. Here, it contends that deep learning tools are suitable means of achieving these objectives. For example, species sampled in automatic recordings can be used to identify the biodiversity of a given place (Buda, M *et al.* 2019). Time labels customised to a species' life cycle can also be used to monitor the timing of a species' presence at any particular site. Then, by including all of this species data and interaction information into food web models and/or concentrating on indicator species, the health and stability of ecosystems may be observed. Furthermore, an evaluation of the value of ecosystem services might assist policymakers in making decisions about management or policy (Han, Z. and Xu, A *et al.* 2021)

For large-scale surveillance, deep learning is also ideal for carrying out landscape analysis. CNNs have been taught to calculate the percent cover for important benthic substrates using high-resolution photos in order to monitor coral reefs (Ardabili, S*et al.* 2020). Convolutional networks with aerial photos are useful for detecting events that alter the terrain, such cotton blooms. Additionally, areas of high conservation significance in Borneo's forest were defined by quantifying the above-ground carbon density using a combination of satellite photography, LIDAR data, and a multi-layer neural network. Deep learning has several possible uses to monitor the effects of human activity, extending beyond the mapping of species and regions of high value for ecosystems and conservation. Using tracking data from industrial fishing vessels, deep neural networks have recently traced the footprint of fisheries (Rolnick, D *et al.* 2022). Additionally, it has been proposed that deep learning algorithms be used to monitor such activities on social media in order to automatically detect photographs of illicit wildlife items in order to prevent illegal trafficking. Given that social media mining has shown to be beneficial for ecological research, including phenological investigations, the application of deep learning for data mining could be readily expanded to other domains (Bentz, J. 2020). To take things a step further, deep learning has already been envisioned as the cornerstone of an automated sensor, drone, and robot ecosystem management system.

13. Prediction Of Global Climate Via Deep Learning

By using climate models, climate scientists are able to anticipate what the future climate might look like and obtain insight into the past. Similar to a virtual Earth, a climate model is created to replicate the real environment in order to help scientists predict potential future scenarios of climate change. (Nam, K. J *et al.* 2021). The computerised representations of the atmosphere, ocean, sea, ice, surfaces, and other processes make up climate models. Climate models represent the climate system using mathematical equations based on physics and computed by highly sophisticated computers; they do not rely on conjecture (Chakrabortty, R et.al 2021). This study introduces a novel approach to global temperature forecasting: a deep convolutional Long Short-Term Memory (LSTM) model. The next-days prediction using Convolutional LSTMs mapping of past climate change to estimate future climate change since the observed changes is one of the model's new advancements. Furthermore, the unsupervised Deep Learning network model is utilised to address challenges related to the identification of climate patterns, and it enhances the architecture of Recurrent Neural Networks (RNNs) by minimising the loss function across several sequence steps.

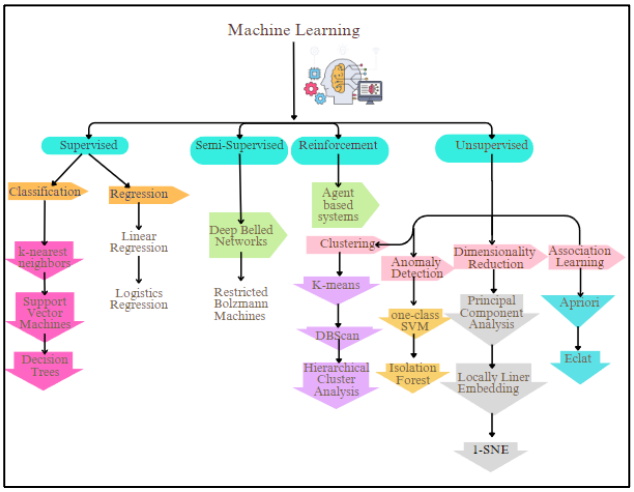


Figure 5. Classification of Machine Learning

However, what if humans could teach computers to learn from historical data and perform tasks that humans can complete far more quickly? This is known as machine learning. Refer to Figure 5 for an illustration of how comprehension and reasoning are just as important as learning. Numerous machine learning algorithms are rather simple to use once they start learning. The prediction model is built using the data, and it can readily forecast for better data when fresh data is received (Wunsch, A *et al.* 2022). Figure 5 shows the types of machine learning. These models will be accurate, and machine learning comes in a variety of forms, including reinforcement learning, unsupervised learning, and supervised learning. Perhaps the algorithm is aware of some of the labelled truth facts. If it was the winner or loser of the match, but only partially. Another example of semi-supervised learning is when an intermediate step is made without knowing if it was a good or terrible move (Bolibar, J. *et al.* 2022). In many of these systems, feedback is crucial, providing a signal to change the system or some other feature.

Prediction is one of the trickiest problems in supervised machine learning. This wish to automate this procedure because it is typically laborious to obtain the target quantities. The prediction is a notable exception because there is no requirement to categorise the data and the data are essentially limitless (Haggag, M *et al.* 2021). Weather prediction is therefore included in the category of semi-supervised learning tasks. The fact that our model has distinct prediction values that are verified by a loss function makes the learning fall under the category of supervised learning. Nonetheless, the training data are consistent with those of unsupervised learning tasks because the values are implicitly provided (Kaack, L et.al 2022). Deep learning is the process of teaching a computer to think like a human brain. Sometimes called deep neural learning or deep neural networking, deep learning is a branch of artificial intelligence that teaches computers to recognise patterns and abstract objects. Consider a toddler learning about dogs to get an idea of deep learning. Assume that the parents respond to their toddler's questions regarding dogs by either saying, "Yes, that is a dog," or "No, that is not a dog." The toddler learns more about canine characteristics, such as ears, tails, hair, and four paws, as he or she points to new objects. The little child is explaining a difficult abstraction.

By constructing a hierarchy, the same idea of a dog may be represented, with each level of abstraction being produced using the knowledge gathered from the layer above it. An example of a neural network in action is a programme that can identify a type of flower from a picture or a song from a person humming it (Wi, S. and Steinschneider, S, 2022). Deep learning applications are seen in speech recognition, translation, and even self-driving car software, in addition to image and song identification.But deep learning is not without its limitations. Deep learning models are solely aware of the data that they have been trained on, and they learn by observation. Figure 6 shows the deep learning. When trained on a tiny or irrelevant dataset, a deep learning model will acquire knowledge in ways that aren't ultimately beneficial (Paschall, M. and Wüstenhagen, R. 2012). Figure 6 illustrates how AI has evolved historically to achieve deep learning.

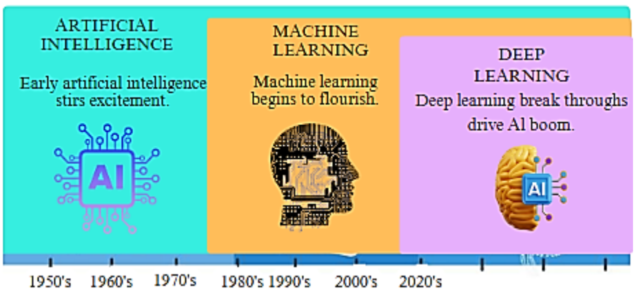


Figure 6. Deep Learning

14. Global climate

The majority of climate models concur that human activity as it stands today will have relatively little impact on the forecast climate in 2050, making the predictions for climate change scarce. Let's travel back in time to 2050 to observe what the planet will look like. There are currently 9.7 billion people on the planet, 500 parts per million of carbon dioxide are present, and global temperatures have risen by 2 degrees since pre-industrial times (Ladi, T. et.al 2022)]. The world's coastal areas are less influenced by this global temperature increase than are interior places. It experiences the biggest temperature spikes from June to August. Because of poor governance, the southern Brazilian Amazon has lost 56% of its forests as sea levels have risen by 30 centimetres this century.

India's health is predicted to be significantly impacted by climate change, with the poorest populations likely to be most severely affected. Malnutrition and related health issues, such as child stunting, are predicted to increase. By 2050, stunting of children is expected to rise by 35% when compared to a world without climate change. The Thar Desert and the Himalayas both have a significant impact on the country's climate. The majority of the Indian subcontinent is kept warmer than most places at similar latitudes by the Himalayas and the Hindu Kush mountains in Pakistan, which block the entry of frigid Central Asian katabatic winds.

In addition to referring to a wider range of alterations to our globe, such as rising sea levels, retreating mountain glaciers, accelerated ice melt in Antarctica,Arctic, and the Greenland, and changes in flower/plant blooming seasons, the term "climate change" also includes global warming. The single greatest hazard to human health is climate change. Because of air pollution, sickness, harsh weather, forced relocation, mental health strains, increasing hunger, and inadequate nutrition in areas where people can't cultivate or get enough food, the effects of climate change are already having a negative influence on people's health. Since the middle of the 20th century, human activity has been responsible for changes in Earth's climate. Burning fossil fuels, in particular, has increased the amount of heat-trapping greenhouse gases in the atmosphere, which has raised Earth's average surface temperature.

The region's rainfall decreased as a result of this extensive deforestation. Because more people live in cities, the world's mean annual precipitation has fallen. locations in the northern hemisphere today typically experience temperatures similar to those of locations located more than 620 miles south thirty years ago (Roy, P. et.al 2022). Warmer temperatures are moving roughly 12 miles northward each year, making it difficult for towns to supply enough water and cooling. Moreover, rising air pollution has made heat stress and respiratory conditions like asthma more common. Cities have put some initiatives into place, but while air conditioning reduces heat discomfort, it also exacerbates air pollution (El-Habil, B. Y. and Abu-Naser, S. S. 2022). There are now improved tree canopies and more reflecting surfaces, which always absorb less heat, to significantly reduce heat-related mortality. Heat waves mostly affect the poor and other vulnerable people, including the elderly. Fortunately, early warning and response mechanisms significantly reduce the death toll from heat waves. Temperatures in Europe have risen annually on average by 4.7 degrees Celsius in the winter and 3.5 degrees Celsius in the summer since 2000.

London, which was formerly cold and wet, is today as hot and dry as Barcelona was in the previous century. Additionally, there has been a rise in infectious disorders such water- and vector-borne illnesses (Malik, I., *et al.* 2023). There is an increase in mental health illnesses like depression as a result of more frequent natural disasters. According to estimates, air pollution will cause 3.3 million premature deaths in 2050 compared to 2010. There are 6.6 million fatalities. Of which 358,000 are from ozone depletion, air pollution-related deaths in metropolitan areas increased by 50% in 2010. The number of lost workdays has increased in many parts of the world around the equator, including southeast Asia, West and central Africa, and central America. There has been an increase of eighteen lost workdays in these regions. Today, the temperature is ninety percent higher in metropolitan surroundings (Zhong, L.,.*et al.* 2023). The economy has been severely impacted by diminished labour capacity, particularly for outside workers.In comparison to 2020, there are 25 million more undernourished children, and the prevalence of stunted growth is rising.

The cost of food is rising quickly, particularly for basics like rice and maize, whose prices have doubled over the past three decades (Chen, X et.al 2019). A significant rise in plant diseases has coincided with a decline in some crops' nutritional value. Iron and zinc levels in rice and soybeans have dropped, as has the protein content of wheat and rice. These have attempted to mitigate this with wheat and peas by diversifying our crop mix and cultivating salt- and drought-resistant plants in greenhouses with drip watering (Ben Othman, A *et al.* 2020). Rainfall and temperature variations are becoming more frequent and destructive, constantly interfering with food production, processing, transport, and marketing.

Unusual weather patterns combined with a rise in pests and illnesses, along with poor dietary habits that lower earning potential and raise health care expenses, can trap families in a multigenerational cycle of poverty. Extreme weather occurrences cause forced migration and intensify tensions surrounding few resources, contributing to the ever-widening gap between the rich and the poor. Food scarcity is closely correlated with political instability, fresh water resources, and fish supplies. Tropical cities saw less temperature rise than cities closer to the poles, but they also saw an increase in the frequency of extreme precipitation events and more severe droughts, which are among the most destructive natural disasters.

14.1. Water and food security problems

Water and food security problems are caused by and made worse by climate conditions. More heatwaves and droughts than ever before have affected areas like the Middle East, which is severely stressing food production. Dust activity has also grown as a result of droughts occurring more frequently and with greater intensity (Sadhukhan, B *et al.* 2022). The primary dust-producing region is North Africa, which is followed by China and

Central Asia. Africa's dust causes algae blooms that damage marine life in the USA's southeast coast. Inhaling dust has a detrimental effect on human health as well, aggravating and inducing cardiopulmonary disorders in living things. Arsenic poisoning, silicosis, asthma, cognitive loss, and Alzheimer's disease are all linked to long-term exposure.

Every year, there are droughts and then there are heavier precipitation events. The latter cause more waterborne illnesses; for instance, heavy rains can lead to sewage overflow, which raises the risk of gastrointestinal illnesses and viral floods in water (Davenport, F. V. and Diffenbaugh, N. S. 2021). A warmer environment increases the risk of contracting vector-borne illnesses in addition to increasing the incidence of waterborne illnesses. This is due to the fact that throughout the first 20 years of the twenty-first century, rising temperatures altered the rates of survival and reproduction of diseases and vectors.

14.2. Global temperature

This must halt the increase in global temperature by 2030; however, if we are unable to do so and miss the deadline by eight years, the trend may then become permanent. The National Aeronautics and Space Administration (NASA) data indicates that the global mean temperature map will rise. Achieving this objective by the UN-set 2030 date will mean keeping the average global temperature below 1.5 degrees Celsius (Jacobson, M. J *et al.* 2017). The biggest carbon-intensive nations—China, the US, India, and Russia—should reduce their emissions first in order to increase the effectiveness of the plan. This can be achieved by completely eliminating carbon emissions. They should be encouraged to do those actions since they will have an impact outside of their own nations (Zhang, Z. and Li, J. 2019). Developing nations ought to help by enhancing their standards of living in order to become future contributors. Big nations can accomplish other things besides this, though.

The global temperature must stop rising continuously by 2030; however, if we are unable to do so and miss the deadline by eight years, the increase may then become permanent. Based on data from the National Aeronautics and Space Administration (NASA), the global mean temperature map will rise (Singh, M et.al 2022). Meanwhile, keeping the average global temperature below 1.5 degrees Celsius is the aim of the 2030 deadline set by the UN. This can be achieved by removing carbon emissions; the nations that emit the most carbon dioxide, such as China, the US, India, and Russia, ought to reduce their emissions first in order for the plan to be more effective. We might be able to solve the system of equations for these properties and each and every one of these grid points, even though handling large datasets is a significant challenge in climate science research—especially since the majority of real-world time series datasets are multivariate and rich in dynamical information of the underlying system (Gerges, F. *et al.* 2022). This requires millions and millions of calculations due to computing and other limitations. Certain processes and climate models, including those that depict clouds, are only loosely defined by representations known as parameterizations (Cho, S. and Lee, Y. W. 2019). These parameterizations contribute significantly to climate uncertainty. The intricate, all-inclusive models have only been created and used by a small group of climate researchers. In order to inform global policymakers about climate change, it is necessary to comprehend the current and projected state of the climate.

14.3. Standard Models of climatic condition

The average monthly temperature is simulated when using the standard models to simulate temperature changes. These models are more challenging to use at the global scale since weather and climatic variations are more pronounced at such scales (Vogel, C *et al.* 2015). Our artificial intelligence (AI)-powered climate model provides scientists with more dependable tools to help them comprehend historical climate change and forecast future changes over an extended period of time.

1. Create a semi-supervised, unsupervised climate prediction model.
2. Introduce a novel learning strategy based on Long Short-Term Memory LSTM that addresses the Deep Long Short-Term Memory (DLSTM) random weight initialization issue.
3. Based on the time series maps, provide a strong forecasting application that might be used to transform those observations into patterns that are readily applied to upcoming projections.
4. Why Assist scientists and decision-makers in their resolve to take action and think about the possible advantages of lowering climate change technology.

15. Recurrent Neural Networks (RNN)

A kind of machine learning model called a neural network essentially has a structure similar to that of the human brain (Markowitz, D. M. et,al, 2018). After ingesting data, neural networks train themselves to identify patterns in the data and forecast the results for each subsequent collection of related data at its foundation. A network of continuing mathematical equations serves as the foundation for a neural network.

The ideal neural network, shown in Figure 4, has an input layer, one or more hidden layers, and an output layer. This diagram illustrates the workings of a basic neural network. One or more features, input variables, or independent variables make up the input layer. These are represented as X1, X2, and so on (Markowitz, D. M. et,al, 2018). Similar to how the output layer is made up of one or more output units, the hidden layer is made up of one or more hidden nodes or hidden units.

Similar to how a given neural network can have as many layers as necessary, the given layer can have as many nodes as desired. In general, additional nodes and layers enable the neural network to perform far more sophisticated calculations. Let's examine an illustration to comprehend your networks. Let's say we have a dog photo and we want to train a neural network to identify the breed of dog by giving it a collection of images representing various dog breeds.

15.1. Interconnected nodes

Since a neural network is just a network of equations, each node in the network is made up of two functions: an activation function, which determines which node in the layer below is activated in the end, and a linear function (Kheir, A. M et.al 2023). When a typical match feature is activated, a number between 1 and 0 is produced. The input image is sent to each node's linear function, which yields a value z. This value Z is then fed to the activation function, which assesses whether or not the distinctive feature matches. Up until it reaches an output, each node ultimately chooses which node in the subsequent layer is activated. This might be referred to as the core essence.

Let's talk about the different kinds of neural networks used in machine learning. There are a few different kinds, but there are three primary kinds that 1. Synthetic Neural Networks As seen in Figure 7, these are the ones that are made up of a group of interconnected nodes that accept one or more inputs and output a number. 2) CNNs, or convolutional neural networks. A CNN is a kind of neural network that, in at least one layer, does not use conventional matrix multiplication but rather mathematical operations such as convolution (Baño-Medina, J. et.al 2021). 3) Refer to Recurrent Neural Networks as a Compact Because of this feature, recurrent neural networks are a sort of n ends where node connections create a digraph along a temporal sequence, enabling them to handle variable length input sequences using their internal memory (Lotz-Sisitka, H et.al 2016). Finally, neural networks are utilised in self-driving cars, character recognition, image compression, stock market prediction, and a host of other fascinating applications. Figure 7 shows the neural networks architecture. RNNs are particularly good at handling sequence data, such as audio recognition or execution.

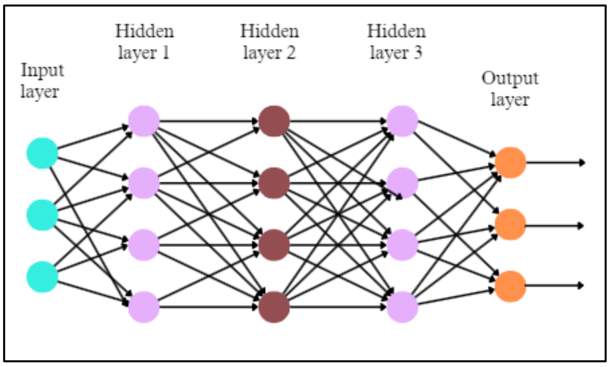


Figure 7. Architecture of Neural Networks

An artificial neural network class called RNNs is focused on techniques for processing sequential data efficiently. An RNN's primary strength is its ability to retain the outcomes of prior computations and apply them to the present calculation.

As these are feeding a series of words into the RNN, as shown in Figure 5, this makes our NN models suited to model context dependencies in inputs of arbitrary length in order to generate a good composition of the input which is the ideal fit for natural language processing applications (Crane-Droesch, A. 2018). Every time a word is input, the state is changed, and as a result, it effectively represents all of the words that have been processed thus far. In addition to the words themselves, the state will also have information about their order (Willi, M *et al.* 2019). Consider the states at each stage when the RNN processes the following sentence:

"Deep learning is hard but fun." This is an example of how deep learning is fed into an RNN. When we feed learning into the RNN, the state has a representation of simply the word deep next. As the RNN continues to extract words from the sequence, it will update the state, which previously contained a representation of only deep, to now contain a representation of deep + learning.

16. Semantic Information

Deep learning is represented in the end state, which is challenging but enjoyable. Because the RNN functions similarly to the human brain, its final state includes both semantic information about the words in the sentence and sequential information about their sequence, making it ideal for understanding the sentence (Shimoda, Y *et al.* 2011). Recurrent neural networks are used for much more than just text generation; they can also be used for machine translation, image captioning, authorship identification, and more which is described in Figure 8. While these applications won't replace humans, it's possible that a neural network could create new, reasonable patient abstracts with more training data in the larger model (Huntingford, C *et al.* 2019).

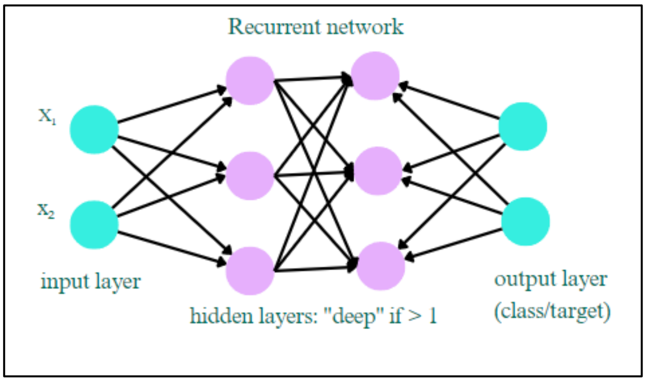


Figure 8. Recurrent Neural Networks

17. Forward pass and Back propagation

Since back propagation is a key component of deep neural network training, let's examine how it affects these three main steps of neural network training to better understand why short-term memory and vanishing gradients are a result of this algorithm's design (Rooney-Varga, J. N et.al 2014). Using a loss function, it first does a forward pass and generates a prediction, which it then compares to the actual data. An assessment of the network's performance degradation is provided by the error value that the loss function outputs which is evaluated in Figure 9. It does back propagation, which determines the gradients for every node in the network, using the error value (Groulx, M *et al.* 2021) . In order for the network to learn from larger amounts of data, its internal weights are adjusted using a metric called the gradient. Larger modifications correspond with a gradient, and vice versa. This is where the issue arises with backpropagation: every node in a layer computes its gradient in relation to the gradients' effects and the layer before it, hence the modifications in the layer before. If it is tiny, the current layer's changes will also be reduced, causing the cost gradients to shrink exponentially.

The vanishing gradient problem, which occurs when internal weights are scarcely modified owing to an extremely small gradient, prevents back propagates down the older layers from learning anything. Let's see how this relates to RRN. Every time step and the current network can be viewed as a layer for RRN training (Groulx, M et.al 2021). Employ a backpropagation technique known as back propagation through time. As the gradient propagates for each time step once more, its value will exponentially shrink. The gradient is then used to adjust the neural network's weights, as seen in Figure 9, enabling it to learn small gradients equate to small adjustments. Because of the disappearing components, this prevents the early layers from learning.

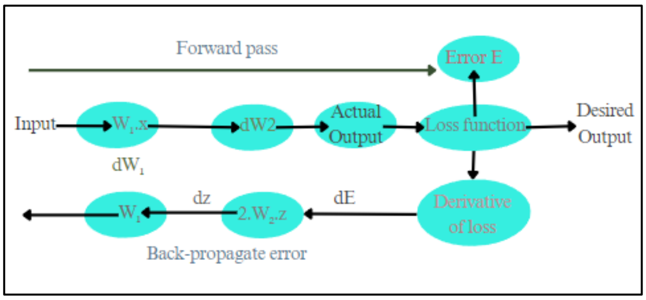


Figure 9. Forward pass and Back propagation

Network access to short-term memory Now, since RNNs have short-term memory problems, how can we address this? Specialised recurrent neural networks were developed, one of which is known as long short-term memory, or LSTM (Palmer, T. and Stevens, B. 2019). Another is known as gated recurrent units, or LSTM, and is essentially used for medications. However, these networks are able to acquire long-term dependencies through the use of mechanisms called gates, which are essentially tensor operations that can determine what data to add or remove from the hidden state. As a result, short-term memory becomes less of a problem for them.

18. Air Pollution Modelling With Deep Learning

A variety of modelling approaches are suitable for forecasting air pollution. The most popular strategy for this is the LSTM approach in particular. Recurrent neural networks (RNNs) include long short-term memory (LSTM) models, which are used to forecast future events based on time series data like meteorological and pollution data (Bauer, P. et.al 2023). The LSTM model uses memory blocks in place of neurons in the typical RNN's hidden layer. The input, forget, and output gates of the LSTM block system allow information to go between the cell and outside of it. The LSTM block system is shown in Figure 10.

The STDL method, which takes temporal and spatial variations into account for prediction, is the second approach that is frequently utilised in this context. As an introduction model, stacked autoencoder models are used to exclude elements that are inherent to air quality (Kumar, S. 2023). The primary concept underlying stacked autoencoders is that the output layer of each autoencoder stacked in a lower layer is connected to the input layer that comes after it. Additionally, spatiotemporal data are employed in DAL models, which primarily rely on feature selection and semi-supervised learning, to improve prediction performance. Along with feature selection in the input and output layers and spatiotemporal semi-supervised learning, DAL is an efficient method.

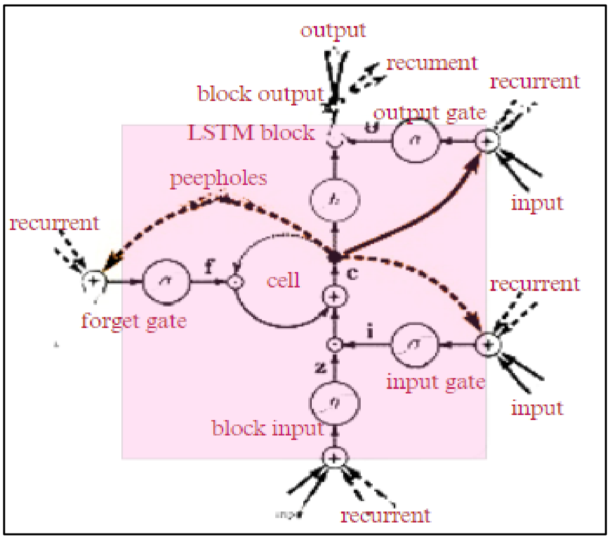


Figure 10. Block system of LSTM models

Additionally, photographs are used to simulate air quality using CNN models. This model comprises two fundamental components: The Rectified Linear Units (ReLU) activation function, which is designed for photo-based air pollution estimate, and the negative log-log classifier, which improves the model's ordinal discriminative capacity.

19. Comparison the results of different studies

Deep learning models were used in a number of research to forecast future air pollution concentrations. Table 1 lists earlier research on the estimate of air pollution. This table shows that models created using LSTM have produced encouraging outcomes. Furthermore, RMSE values show how well the models perform, and research by (Sham, N. M. and Mohamed, A.2022) has produced more effective outcomes. For both short and long time periods, more successful outcomes have been achieved in models built with various techniques.

Using deep learning to model air pollution is a novel idea. Deep learning-based air pollution prediction could produce almost precise predictions in the future. Larger initiatives may be established in this field and the lack of applicability to air pollution forecasting could be mitigated with the use of deep learning. Deep learning can be used to predict air pollution using a variety of huge data sets, including images, audio files, and numerical data. For example, STDL, LSTM, CNN, and DAL are some of the techniques employed here. The data and algorithms they employ determine how effective they are. The outcomes of using deep learning algorithms for air pollution estimate are more successful than those of using other techniques such as artificial neural networks and fuzzy logic.

Additionally, we would want to highlight a viable avenue for solving the air pollution prediction problem: According to recent research, generative adversarial networks, or GANs, are particularly effective at producing content through two competing networks: one that creates synthetic forecasts and the other that separates real data from fake data (Jayamala, R et.al). It is anticipated that the interactions between these two networks will yield a model with more predictive power than the most advanced deep learning methods. We have the following insight into this expectation: While learning the behaviour of real data is vital, predictive models tend to perform better when given examples of how real data behaves when complex data synthesisers are present.

Table 1. Previous studies conducted with deep learning for air pollution estimates

Reference	Pollutants	Evaluation Criteria	Prediction Performance	Modelling Method
(Kumar, S. 2023)	PM2.5, PM10	Average Error (AE)	AE 0.606 (PM2.5)	CNN
			AE 0.411 (PM10)	
(Palmer, T. and Stevens, B. 2019)	PM2.5	RMSE	RMSE 0.0667 (1-12 hour)	DAL
			RMSE 0.0877 (37-48 hour)	
(Lotz-Sisitka, H et.al 2016).	PM2.5	Root Mean SquareError (RMSE)	RMSE 12.41 (8 hours)	LSTM
			RMSE 13.54 (24 hours)	
(Sadhukhan, B *et al.* 2022)	O_3, NO_2	RMSE, Mean Absolute Error(MAE)	RMSE 3.26 (O_3)	LSTM
			MAE 2.81 (O_3)	
			RMSE 3.76 (NO_2)	
			MAE 3.11 (NO_2)	
(Kheir, A. M et.al 2023)	PM2.5	RMSE, R2	RMSE 44.15 (5 hours)	LSTM
			R2 0.689 (5 hours)	
			RMSE 108.14 (120 hours)	
			R2 -0.328 (120 hours)	
(Chen, Z. *et al.* 2021).	PM2.5	RMSE, MAE, Mean Absolute Percentage Error(MAPE)	RMSE 14.96	STDL
			MAE 9.00	
			MAPE 21.75%	

20. Implementing Deep Le Arning: Challeng Es And Guidelines

Although deep learning techniques are strong and have great potential for ecologists, there are several considerations that must be made before selecting to use them. In this segment, we list typical queries that come up when experimenting with deep learning. To assist ecologists in determining when deep learning would be advantageous for their research, we also offer guidelines and recommendations. But since this part is not meant to be all-inclusive, it is a good idea to work with or consult computer scientists prior to applying deep learning, just as you would with statisticians prior to study design.

21. Regression

Additionally, deep learning has proven effective when used for counting or forecasting future events, as well as applications involving inference of continuous variables. A regression task called object detection is used in many research involving image or video data to locate objects in images or video frames by locating bounding box coordinates (Graving, J. M et.al 2019). This is frequently coupled with categorization. Pest and disease diagnosis as well as pest identification and counting are frequent agricultural applications. In one investigation, text diagnosis creation was paired with tomato disease classification and location. Moreover, object detection has been extended to ecosystem scale and used in resource management, conservation, and diversity evaluation. Using drone and satellite photos, for instance, to count marine turtles and whales are two examples (Borowicz, A et.al 2019). For the purpose of mapping vegetation, additional applications integrate digital imagery with LiDAR and other remote sensing or geospatial data. Systems for tracking wildlife in real time can incorporate object detection by utilising information from microphones and video traps.

In environment mapping, regression-based techniques other than object detection are also frequently used. Numerous open-source toolkits have been created to track movement and body posture in video recordings without causing any harm to the subject. We discuss neural networks together because they serve comparable purposes, even though they use different methods to achieve it—regression, classification, modelling, or a mix of these (Weinstein, B. G *et al.* 2019). A variety of solutions are available, ranging from species-specific programmes like DeepFly3D for Drosophila and OpenMonkey Studio for macaques to general frameworks like DeepLabCut and DeepPoseKit that may be used with any species and provide three-dimensional and/or multi-animal tracking. In addition to being utilised for behavioural analysis of spatial trajectories, deep learning is also used to improve well-established computer vision techniques for tracking the spatial position of animals, such as tag recognition or marker identification. Neural networks are used to quantify the phenotypic similarities of animals in addition to detecting or tracking individual animals. Since the 1990s, reactions to environmental variables were predicted through the use of dense neural networks (Safonova, A *et al*. 2019). In recent times, temporal ecological information has been analysed using recurrent neural networks and related techniques. suggested a broad method for predicting and classifying ecological time-series data that makes use of automatic network architecture selection for the desired objective. It suggested using presence/absence data to predict the dynamics of colonisation and extinction using an RNN technique.

A rapidly expanding trend is the use of machine learning to infer population genetic characteristics. According to one study, neural networks can detect introgressed loci and positive selection on simulated data, as well as estimate population genetic variables including mutation rates, population sizes, and recombination rates. That work showed that CNNs can predict recombination rates in autotetraploid genomes, for example, or estimate population genetic parameters for situations for which mechanistic models are unavailable.

21.1. Modelling

Ecological modelling with deep learning has a somewhat extensive history. Unsupervised grouping and reduction in dimensionality of community ecological data and environmental factors using neural networks was a prominent early technique. The modelling of species interactions and distributions also makes use of deep learning (Moniruzzaman, M. et.al 2019). Although reliable species distribution models can be produced by deep neural networks, other machine learning techniques outperform them when given limited training data. It created a method that uses latent variables limited by species co-occurrence to forecast species interactions. For the investigation of adaptive problems like resource allocation, reinforcement learning is an attractive paradigm .

The study of matter and energy movements in ecosystems, which arise from interactions between biotic and abiotic system components and take place over a variety of geographical and temporal scales, is known as ecosystem ecology. The literature in Ecosystems attests to the field's wide scope and its interconnections with almost all other ecological subdisciplines. We will look at three main areas to show the variety of uses of deep learning in ecosystem ecology: data analysis defining fluxes of energy and matter, picture analysis and processing, and combining with ecological and environmental simulations. Although many of the case studies researchers have used are related to other aspects of ecology, they are nevertheless consistent with basic questions of ecosystem ecology. Similar to this, many of the benefits and drawbacks of utilising DL are cross-domain in nature, encompassing applications in other subfields of ecology such as automated translation and large-scale text analysis that have the ability to reduce biases in literature syntheses.

A study that combined neural networks and reinforcement learning examined how predator-prey dynamics were affected by individual agents' acquisition of hunting or avoidance skills. Numerous research employed innovative neural network techniques to investigate sexual selection and imitation. Examples include analysing the visual cues that pigeons use to differentiate wasps from flies, quantifying plant-insect mimicry in fossils, and studying the dynamics of Batesian mimicry using developing populations of a model and several mimics (Wang, H., et.al 2019). It tested the assumptions of the sensory drive theory and quantified the patterns of male and female fish in response to their surroundings using neural networks.

Variational autoencoders, a type of neural network, has been used for unsupervised grouping in unsupervised learning and population structure visualisation. Deep learning is starting to be used for local-ancestry inference, which identifies populations from which a genetic locus descended, and sample origin prediction based on genetic variation as the significance of the spatial component in population genetics is being highlighted more and more. In order to do this, artificial human genomic sequences with known ancestry must be created using generative adversarial networks [30]. Additionally, GANs have been used to model vegetation succession to learn about species interactions, to add false visuals to training data to enhance it, and to replicate realistic population genetic data for inference of population genetic parameters.

21.2. Which is better, deep learning or machine learning?

Why use deep learning instead of "traditional" machine learning and how is it different are two of the most frequently asked topics. The method used to extract features from the data is where this method differs most from other approaches. Traditional machine learning algorithms need human supervision for feature extraction; in contrast, deep learning tools, because of their multilayered structure, are able to learn very complicated representations of data on their own. As a result, they are simpler to utilise when consumers are unfamiliar with the characteristics that need to be detected (Guo, Q et.al 2020). The exceptional precision attained in identification and classification assignments also leads to one of the primary justifications for utilising deep learning: performance. These outcomes, however, are reliant on the availability of a sizable labelled dataset that can be utilised to train the algorithms for feature extraction from the data. Compared to conventional methods, the training process might take a lot longer and use a lot more computer resources. Thus, deep learning is particularly suitable for large-scale data analysis, and it excels at complicated tasks like speech/sound identification and image categorization.

22. Conclusions

Deep learning can be helpful for ecological research because, like other machine learning computations, it offers practical ways to evaluate nonlinear data with intricate connections. When it comes to automatically detecting things of interest in data—like animals in photos—deep learning algorithms really shine when they are given samples of what to look for. They are the go-to tools for jobs involving recognising and categorising things because they can accomplish it with exceptional precision. Due to their effectiveness and simplicity in training, supervised methods have received the majority of attention thus far. However, advancements in unsupervised learning are anticipated, which may eliminate the requirement for annotated datasets entirely. Ecologists can expect a lot from deep learning. Even though the techniques are still in their infancy, they have already been used to a wide range of ecological issues and can be highly helpful resources for managers, conservationists, or decision-makers as they offer a quick, unbiased, and trustworthy method of analysing massive volumes of monitoring data. Applications are not limited to ecology; deep learning may also prove beneficial in the study of evolution and general biology. However, creating a deep learning solution is still a difficult effort, so ecologists should give it some thought to see if this is the best tool for the job. Before pursuing deep learning, one should take into account the requirements regarding training datasets, training duration, development complexity, and processing power.

Artificial intelligence will be used more and more often to examine data as ecology moves into the big data space. Ecologists will therefore need to become proficient programmers and/or mathematicians with access to these resources. Although this may initially appear frightening, we think that there is a single, straightforward way to overcome this difficulty: interdisciplinary cooperation. Improved communication between ecologists and computer scientists may also result in new methods and collaborations for the categorization and analysis of data, offering fresh perspectives for both basic and applied ecological research. Like many others before us, we also strongly advocate for the open sharing of datasets and code whenever possible in order to facilitate the use of sophisticated technologies like deep learning in ecological research and make it faster, simpler, and directly repeatable in the future. We think that deep learning may develop into a useful and accessible reference tool for ecologists as a result of software becoming more robust and user-friendly, experience building, and the availability of shared resources like datasets.

23. Abbreviation

ANN	Artificial Neural Networks
CNN	Convolutional Neural Network
RNN	Recurrent Neural Networks
CE	Cross Entropy
LSTM	Long Short-Term Memory networks
GRU	Gated Recurrent Units
GAN	Generative Adversarial Network
DNN	Dense Neural Networks
VAE	Variational Autoencoders
NASA	National Aeronautics and Space Administration
DLSTM	Deep Long Short-Term Memory
STDL	Spatio Temporal Deep Learning
DAL	Deep Air Learning
ReLU	Rectified Linear Units

Competing interests

The authors declare that they have no competing interests.

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Authors' contribution

Author 1 and 2 helps to find the pollution factor in environment.

Author 3 supports to find materials and results part in this manuscript.

Author 4 develops the discussion about previous studies.

Author 5 help to enhanced the application of deep learning

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