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# Applications of Deep learning and cross media intelligence for decision making in ecology model using hybrid expert system

**S. Balapriya[1] and N. Srinivasan[2]**

***[1]Sathyabama University, Chennai, T.N., India***
***[2]Bassure Solutions Pvt. Ltd, Chennai, T.N., India***

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**ABSTRACT**

As the planet warms, the effects of climate change are going to become more severe. When compared to the previous year, the number of weather and disaster events has doubled. Currently, 20% of species are threatened with extinction, and that percentage might climb to 50% in the next century. By 2100, average global temperatures are expected to be 3 $^{o}$C higher than they were before the Industrial Revolution. As the most sensible and responsible members of our ecosystem, we must consider all options influencing the biosphere's equations. Environmental challenges have spawned debates, discussions, public awareness campaigns, and public indignation in recent years, activating interest in new technology such as Artificial Intelligence. In this post, we'll look at Artificial Intelligence (AI) as a new technique to assist us better maintain the planet "Earth". Here we analyse on how to wisely use a human-made intelligent system called an "expert system" as an alternative approach to save our environment. This article also focuses on artificial intelligence and understanding how the human mind organizes and processes large amounts of data.

***Key words :*** *Deep learning, Cross media intelligence, Hybrid expert system*

## Introduction

Ecology is largely based on the collection of increasingly more data. Ecologists are always interested to point out the complexity of ecological systems such as:

1. The difficulty of conducting controlled and replicated experiments
2. The impossibility of experimenting on large-scale systems
3. The bewildering array of ecological behavior that are observed
4. The exasperating ability of living organisms to acclimate, adapt, and evolve.

Despite all of the above factors, with the exception of computer simulation modeling, ecologists have invented or adapted essentially no computer-based tools to aid them. The ecological knowledge base, which spans everything from physiology to the biosphere, is already massive and continues to increase. This huge information forces us to devise new and more effective methods of organizing, processing, and interpreting ecological data, focusing on and facilitating ecological reasoning rather than data reduction.

The high-speed, computerized tools and approaches emerging from AI research could help ecologists understand and reason about ecological complexity and combine the theory and procedures

([1]Research Scholar, [2]Sr. Consultant)
**Corresponding author's email:** s.balapriya@gmail.com, srinin@bassure.com

for applying ecological knowledge to real-world situations. Although more research and testing is required to define the scientific role of AI in ecology, it is certain that some of the techniques will become commonplace in the tool-set of ecologists.

**Related Works**

Artificial intelligence (AI) is a subfield of computer science that focuses on utilizing computational models to better understand how people think. Expert systems (ES) are involved in designing models for complicated search methods, knowledge representation, logical and probabilistic reasoning, learning, robotics, and other fields of research. Computer technologies created in one or more related domains are referred to as AI or ES techniques. The creation of expert systems prompted a slew of other academics to look into AI's possible applications in their domains, and the same approach or technique can be applied to ecological study as well.


**Fig. 1.** Model Description

Species distribution models (SDMs) are commonly used in ecology, biogeography, and conservation biology to assess correlations between environmental variables and species occurrence data and generate predictions about how their distributions change over time. Machine learning technologies are increasingly being used in this field to create and validate SDMs. As a result, model accuracy has constantly improved, but model interpretability, such as the relative relevance of predictor variables, has not always kept up. We use explainable AI (xAI), an emerging sub discipline of artificial intelligence, as a toolkit for better interpreting SDMs.

The goal of xAI is to decode the behavior of complex statistical or machine learning models (e.g., neural networks, random forests, and boosted regression trees) and create more transparent and understandable SDM predictions. We explain how xAI works and present a list of tools that may be used to help ecological modelers better comprehend complex model behavior at various sizes.

Before digging into the mechanics of computing, an ecologist should be able to think largely about the ecological problem in an ecological computing environment. The creation of customized computing environments allows researchers to focus on the issue domain rather than the mechanics of computer manipulation. However, rather than understanding the problem, AI technologies have an impact on how ecologists structure, create, and apply models.

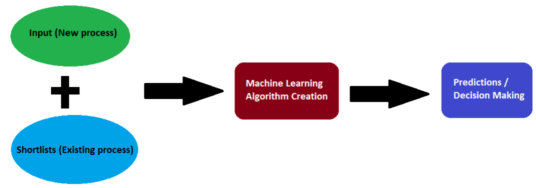



**Fig. 2.** Input/Output Process

Many ecological computer models are just techniques for generating numerical approximations to the solutions of many models that are difficult to parameterize and run, let alone understand the resultant output, for non-modelers. This is the primary reason why the majority of the research effort is spent developing and debugging the model, with considerably less time spent considering the underlying problem that prompted the modeling effort in the first place. This is the first step in modeling the environments that will be taken into account.

The type of knowledge that can be represented and how knowledge is arranged are the two key analytical phases required in an AI based computing environment.The object-oriented programming systems are used in the second stage (OOPS). Ecological entities are typically represented by variables or vectors in today's modeling technologies. Any type of fish, for example, might be represented in an ocean model by a vector of values indicating its age, category, size, and minerals connected with it. However, because knowledge representation via equations does not allow for the definition of a fish object, there is no such object in the model. Furthermore, there is no specific data structure that links these values to a fish. It appears to be far more natural to construct a model utilizing ecological things that ecologists are already familiar with. Object-oriented programming is built on the concept of a collection of interconnected objects that are meaningfully specified in a scientific context. For hierarchical models of ecological systems, some object-oriented programming techniques may be very useful.

Machine learning is a branch of artificial intelligence that relies on computational models learning patterns from input data and improving performance on specific data analysis tasks over time. It can include a variety of techniques, such as deep learning, which makes use of data structures known as "deep artificial neural networks." Training a new model is computationally expensive and time-consuming since one deep neural network can have thousands of internal parameters. Transfer learning is a technique that allows pre-built "off-the-shelf" models to be fine-tuned to a new issue and dataset. This method reduces the time it takes to train a model from scratch and has made deep learning more accessible to non-expert users.

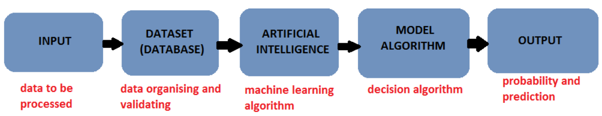



**Fig. 3.** Work Flow

With the help of open-source software libraries that enable programming interfaces for deep learning libraries, deep neural networks can be developed in a variety of computer languages. Deep learning can be implemented on a computer utilizing either graphics processing units (GPUs) or the central processing unit (CPU). GPUs are more suitable for running deep learning models than CPU processing modules on a device since they are optimized for parallel arithmetic operations. Cloud-based processing is another option for computation that does not require local hardware. Many prominent platforms now offer options to run deep learning algorithms on the cloud.

## Quantitative and Qualitative of Scientific Data Integration

When articulated orally and diagrammatically, ecological information is hazy (or fussy). Ecologists lack the technology needed to put their considerable knowledge to use in a meaningful way. The essence of ecology has yet to be codified into a collection of mathematical equations. It's pointless to wait for ecology to become largely quantitative while neglecting the predictive power of qualitative information in the meantime.

In truth, ecologists have a lot of information in their heads, but there aren't many ways to make it clear, well-organized, and computer-processable. Artificial intelligence research may provide tools for manipulating qualitative knowledge in the form of symbolic computing techniques. Many ecological concerns, particularly those concerning decision-making, may be answered in terms of 'better or worse, more or less, sooner or later,' and so on.

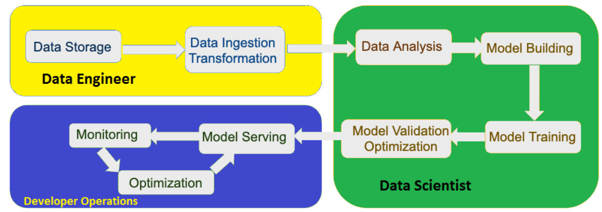



**Fig. 4.** Developer Process

The pursuit of quantitative knowledge must continue to uncover ecological linkages that may be articulated and manipulated using mathematics. To deal with the complexity of ecological and environmental systems, the task is to combine quantitative and qualitative information. Even when quantitative predictions are impossible, qualitative predictions can be made that are scientifically legitimate. To arrive at a qualitative prediction or judgement, quantitative methods are frequently applied. Estimates, projections, and choices must be made in both scientific and managerial contexts when quantitative tools are inadequate or unavailable.

## Conceptual Model Development

After all, science is the search for the laws that govern how nature behaves. We have evidence that describes the rules that govern the operation of ecological systems. Because ecological systems are so complicated, it's not unrealistic to believe that hundreds or thousands of rules are required to describe, say, the behaviour of a salt marsh. Any tool that can assist us in discovering the logical ramifications of complex ecological chains of reasoning must be used.

AI technologies may prove valuable in 3 ways for theoretical development in the future:

- Computer-compatible knowledge organization that includes both qualitative and quantitative ecological model measures
- fast evaluation of hypotheses, assumptions, or other concepts
- assessing the logical consistency and consequences of long and intricate reasoning paths

## Ecology Model Management

Expert systems are going to play an increasingly

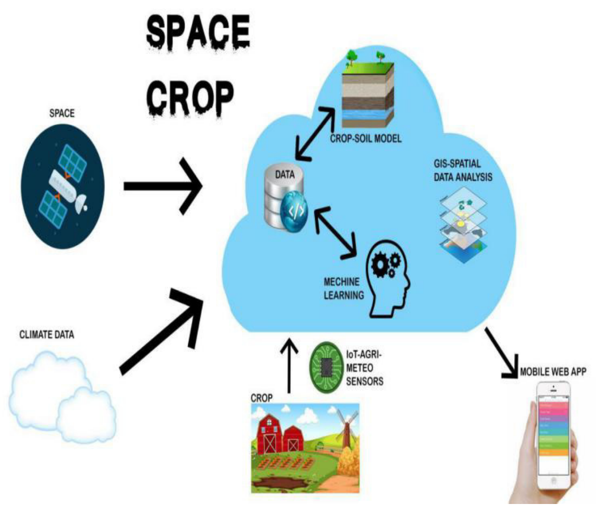



**Fig. 5.** Sample data

important role in this field. It's one of the few ways to bring sound ecological information into the management environment that's easily observable. All resource management agencies engage in planning activities that AI or ES technologies can help to improve. The influence of ecological science on decision-making can be expanded to the extent that ecological factors can be included into these systems. Resource applications can also be used to assess the consequences of different management strategies. While policy analysis has received little attention in ecological circles, it is expected to become more significant as ecological discoveries are translated into management practices.

The integration and collaboration of biological-intelligence systems with machine-intelligence systems is required for research into human-machine hybrid intelligence, resulting in greater degrees of intelligence. Because humans and robots collaborate, this advancement could lead to improved problem-solving and decision-making abilities. Wearable gadgets, robotics, aided education, and items connected to human-machine integration are all possible applications.

Natural resource management has become a challenging, if not impossible, task. This is due in part to a failure to effectively predict social dynamics within social-ecological systems, particularly in situations where human livelihoods and long-term conservation are at odds. Multiple interacting stakeholders with unique and potentially opposing values, interests, and aims make decisions in such systems. New techniques that can manage the complexity behind the causes and consequences of human decision making are needed to better forecast social dynamics in these systems.

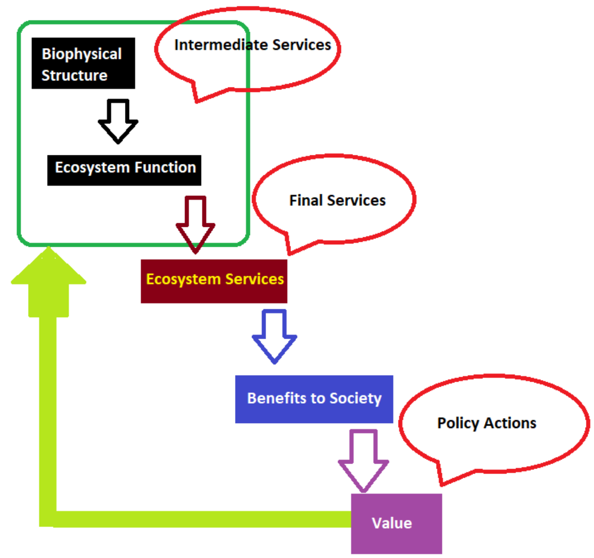
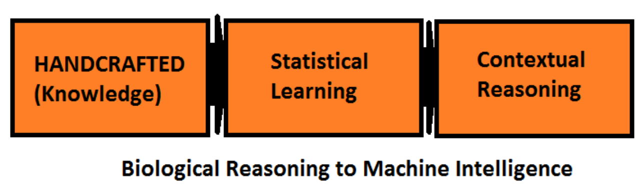



**Fig. 6.** Ecology Model Management

Games are increasingly being employed in social-ecological research as helpful instruments for investigating human decision-making. Researchers can use games to better study how people make strategic decisions in complex settings with trade-offs, conflict, and uncertainty. Commercially successful computer games have the capability to do this, as well as an audience for games that require social-ecological decision-making. This is the ideal time to consider these games as a means of advancing research game development, data gathering, social-ecological models, and, ultimately, real-world solutions.




## Conclusion

Artificial intelligence approaches are now being researched for use in environmental science. Studies are being focused on how to employ AI or ES technology to advance ecological research at this early stage of development. Over the next decade, the role that this technology can play in ecology will be determined. Many present hopes will be dashed, but a few will come true, resulting in important instruments for ecological research and application of ecological knowledge to management.

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