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Advancing biodiversity education: The role of deep learning in fish identification

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Abstract

This study examines trends in deep learning applications for fish identification, highlighting its significance for biodiversity education and conservation. Accurate identification of fish species enhances students' understanding of aquatic ecosystems and promotes environmental sustainability. A bibliometric approach was employed to analyze 737 articles published between 2014 and 2024, using keyword mapping, citation patterns, and inter-article linkages in the VOSviewer application. The analysis revealed that deep learning techniques, particularly Convolutional Neural Networks, improve the accuracy of fish species identification compared to traditional methods. Despite these advances, the integration of such technologies in educational contexts remains limited, representing a notable research gap. Based on these findings, the study advocates for the incorporation of deep learning tools into biodiversity education curricula to foster interactive, efficient, and technology-driven learning experiences. The research underscores the potential of leveraging advanced computational models to enhance both pedagogical practices and conservation efforts. By bridging artificial intelligence with environmental education, this study provides a framework for developing innovative strategies that support student learning, improve ecological literacy, and contribute to the sustainable management of fisheries resources.

Keywords: Biodiversity education; convolutional neural networks; deep learning; fish identification; technology integration.

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1. INTRODUCTION

Research on deep learning-based fish identification is increasingly important amidst the rapid development of educational technology and biodiversity conservation. In the context of education, the ability to accurately and efficiently identify fish species has strategic value in improving students' understanding of aquatic ecosystems. In addition, this research also has a direct impact on the conservation of fisheries resources and monitoring of fish populations, which is important for maintaining ecosystem balance and supporting environmental sustainability. Recent advances in deep learning models, particularly Convolutional Neural Networks (CNNs), have shown robust performance in classifying fish species and supporting large-scale biodiversity monitoring applications (Mohammadisabet et al., 2025)

Biodiversity is one of the fundamental aspects in the study of biology and ecology, and fish are one of the animal groups that have tremendous diversity. However, manual fish identification faces many challenges, such as limited data, high morphological variation, and individual skills in classifying species. In recent years, deep learning has emerged as a potential solution to overcome these challenges by offering higher accuracy than traditional methods. Deep learning, particularly Convolutional Neural Networks (CNNs), has been widely used in image and video classification for fish species identification (Zhang & Wang, 2024). Enhanced deep learning approaches integrating data augmentation and optimized CNN architectures have achieved very high accuracy (above 98 %) in underwater fish classification tasks, demonstrating the effectiveness of these methods for ecological analysis and monitoring (Siri et al., 2024).

A major problem in fish identification is the low accuracy and efficiency of conventional methods, especially in educational contexts where limited resources and time hinder the learning process. Many previous studies have focused on developing deep learning models to overcome this challenge, but there are still some obstacles, such as limitations in the application of this technology in a wider educational environment.

Previous studies have shown that the use of CNNs can improve accuracy in fish classification compared to traditional methods. For example, Robillard et al., (2023) achieved 97.99% accuracy in Amazonian fish species identification using advanced deep learning models. In addition, the data augmentation method developed by Ben Tamou et al., (2022) also successfully improved model performance by reducing overfitting. However, most of these studies are still limited to applications in laboratories or controlled environments, so their use on a wider scale, such as education, still needs to be studied further. More specific research shows that optimizing model parameters, such as input image size, can improve identification accuracy (Iwahara et al., 2024). In addition, a comparison of various CNN architectures, such as VGG16 and MobileNet, showed that proper model selection can significantly affect classification performance (Hindarto, 2023). These studies provide important insights for the application of deep learning in education. Students need to understand the strengths and weaknesses of each model for their research projects.

While many studies have explored the application of deep learning in fish identification, there are still gaps that need to be addressed. Not many studies have explored the integration of deep learning in educational curricula, especially related to biodiversity. This is an obstacle to the optimal utilization of this technology for educational purposes. Emerging research on indigenous fish species identification using real-world datasets and deep learning shows the potential for expanding these methods beyond controlled lab settings, offering opportunities for ecological education and community science (Terefe et al., 2025)

This research offers a new hypothesis that the use of deep learning, especially in an educational context, can improve students' understanding of biodiversity by providing more interactive and efficient learning tools.

The analysis will also show how research trends related to deep learning and fish identification have evolved and how these can be applied in educational settings.

The scope of this research includes bibliometric analysis using VOS Viewer to identify patterns and trends in deep learning research for fish identification from 2014 to 2024. The research will focus on visualizing the research network to identify key areas where deep learning can be effectively integrated into educational practices. The analysis will also include case studies of the use of deep learning models in educational contexts to illustrate the practical benefits that can be gained from the integration of this technology in biodiversity education curricula.

1.1. Purpose of study

This study aims to analyze scientific publications related to the use of deep learning in fish identification on Google Scholar over the past ten years, from 2014 to 2024. This analysis will be conducted using the VOS Viewer application to map research trends and identify opportunities for the integration of this technology into biodiversity education. This research is expected to significantly contribute to the development of more innovative and efficient technology-based education strategies, as well as support conservation efforts.

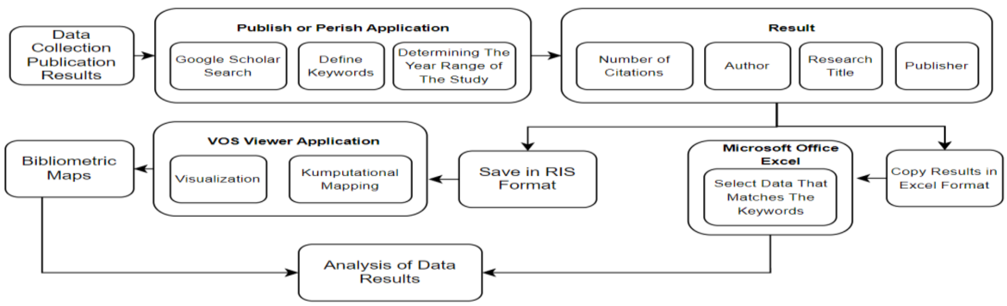
2. METHODS AND MATERIALS

This research was conducted by utilizing articles published and indexed by Google Scholar. The first step in this research method was data collection using the Publish or Perish application. This application was used to review literature related to the predetermined topics, namely "Deep Learning" and "fish identification." The collected articles were limited to journals published between 2014 and 2024, and all data were gathered in May 2024.

The data collection process through Publish or Perish involved searching for articles using specified keywords, setting the research year range, and identifying various important information from the discovered articles. The information collected included the number of citations, author names, research titles, publication year, and the article's publisher. The collected data were exported in two formats, namely Comma Separated Values (.csv) and Research Information System (.ris), which were then used for further analysis. After the data collection process, the exported articles were processed using Microsoft Excel. Excel was used to filter data that matched the keywords used in the research. The data were then processed and organized into a format ready for further analysis. More detailed steps can be seen in Figure 1.

Figure 1

Architecture of bibliometric mapping stages



The next step in this research method is the bibliometric mapping analysis conducted using the VOSviewer software. VOSviewer assists in visualizing the relationships between articles and keywords through co-citation mapping. Three variations of visualizations produced at this stage are network visualization, overlay visualization, and density visualization. Network visualization shows how articles are interconnected through shared citations, overlay visualization displays the trend development based on the emergence of keywords over time, and density visualization illustrates the density of keywords within the mapped articles.

During this process, researchers filter the frequency of keywords so that only those appearing at least 5 times are included in the analysis. After the filtering process, a total of 261 relevant phrases were obtained after removing irrelevant keywords. The results of this computational mapping analysis are then further analyzed to identify research trends in the field of Deep Learning in the context of fish identification. These results provide insights into how research topics have evolved, allowing researchers to identify the most relevant and influential research areas within the analyzed literature.

3. RESULTS

The total number of articles meeting the research criteria is approximately 737, based on data searches conducted in the Google Scholar database using the Publish or Perish reference management program. The metadata obtained includes the author's name, title, year, journal name, number of citations, publisher, relationships between articles, and related URLs. Table 1 presents a sample of the data used in the VOSviewer analysis for this study, consisting of 20 articles with the highest number of citations. The total citations for all articles in this study amount to 139,989, with an average of 77.19 citations per year, 169.19 citations per article, and an average of 3.69 authors per article.

The data obtained from 20 studies cover various scientific topics, ranging from ecology to machine learning. This research focuses on the application of advanced technologies, such as deep learning and machine learning, to address challenges in various fields. Some of these include exploring the impact of invasive species, developing deep learning models for gene expression prediction, and analyzing animal behavior using machine learning.

In the field of ecology, the highlighted studies include species and behavior identification using deep learning, classification of animal behavior using camera trap images, and functional ecological approaches to fish conservation for ecosystem services. Additionally, there are studies exploring the use of environmental DNA (eDNA) to evaluate biodiversity in marine ecosystems and the impact of hybridization on native trout populations and invasive trout.

Other research focuses on genomic technologies for wildlife conservation and the use of machine learning in the drug discovery process. There is also a review of the application of optimization algorithms, such as Artificial Fish Swarm Optimization, and studies on deep learning methods for the automatic identification of plant diseases.

Overall, the summary of this research demonstrates the use of advanced technologies, such as machine learning and deep learning, to solve complex problems in ecology, biology, and technology, emphasizing the importance of cross-disciplinary collaboration in enhancing knowledge and research methods.

Table 1

Top 10 articles on deep learning in fish detection

No	Ref	Citation	Objective	Data Subject	Method
1	(Havel et al., 2015)	550	Reviewing known aspects of aquatic invasive species (AIS) and exploring new challenges and questions related to AIS impacts on freshwater ecosystems.	Invasive species in freshwater ecosystems and their impact on community structure and ecosystem function.	Literature review, AIS impact analysis, human role in AIS spread, and species invasion characteristics in freshwater ecosystems.
2	(Avsec et al., 2021)	546	Developing the deep learning model Enformer to enhance gene expression prediction by utilizing long-range interactions in the genome.	Human and mouse genomic data, including diverse epigenetic and transcription datasets.	Using a self-attention neural network architecture to predict thousands of epigenetic and transcription datasets in multitask settings.
3	(La Notte et al., 2017)	502	Addressing ambiguities in ecosystem service classification using a systems ecology perspective and cascade framework.	Classification of ecosystem services and existing ecological theory approaches.	Literature review, use of the cascade framework, and systems ecology concepts to improve definitions and terminology of ecosystem services.
4	(Valletta et al., 2017)	484	Introducing machine learning (ML) methods to animal behavior researchers for analyzing complex behavioral data, illustrated through case studies.	Complex animal behavior data, including images, GPS data, accelerometer data, and audio recordings.	Literature review, introduction of supervised and unsupervised learning methods, and development of data analysis workflows for three animal behavior case studies.
5	(Neshat et al., 2014)	460	Reviewing Artificial Fish Swarm Optimization (AFSO) algorithms, their evolution, improvements, and applications in various fields such as optimization, control, image processing, and others.	AFSO optimization algorithms, hybrid methods combining AFSO with other methods such as PSO, fuzzy logic, and cellular learning automata.	Literature study and comparative analysis of various optimization methods related to AFSO, along with experiments to test the performance of the developed hybrid methods.
6	(Christin et al., 2019)	455	Reviewing deep learning implementation in ecology for species identification, animal behavior classification, and biodiversity estimation.	Deep learning algorithms, such as convolutional neural networks (CNN) applied to images, audio recordings, and videos in ecology.	Literature review, analysis of articles using deep learning in ecology, including species identification, animal behavior classification, and biodiversity estimation.
7	(Ekins et al., 2019)	445	Using machine learning to improve the efficiency and effectiveness of the drug discovery and development process from start to finish.	Machine learning methods applied in drug discovery, including naive Bayesian, support vector machines, and deep neural networks, along with bioactivity datasets.	Literature study and experiments using various machine learning methods to analyze bioactivity data, develop predictive models, and test their effectiveness.
8	(Silva et al., 2018)	442	Identifying knowledge gaps and providing a roadmap for priority research and technical development in fish passage science, engineering, and practice.	Scientists from various fields such as biology, ecology, physiology, ecohydraulics, and engineering from continents (North and South America, Europe, Africa, Australia).	Literature study and collaboration among 17 experts from various disciplines to identify knowledge gaps and formulate research priorities and technology development in fish passage.
9	(Port et al., 2016)	437	Evaluating vertebrate biodiversity in kelp forest ecosystems using environmental DNA (eDNA).	eDNA data and visual surveys of vertebrate fauna in various marine habitats around the Monterey Bay kelp forest ecosystem, California.	eDNA survey using PCR primers on mitochondrial 12S rRNA gene and comparison with scuba visual surveys.
10	(Tabak et al., 2019)	414	Developing and testing machine learning models to classify	Camera trap images were collected from five locations in	Training deep learning models using convolutional neural networks with

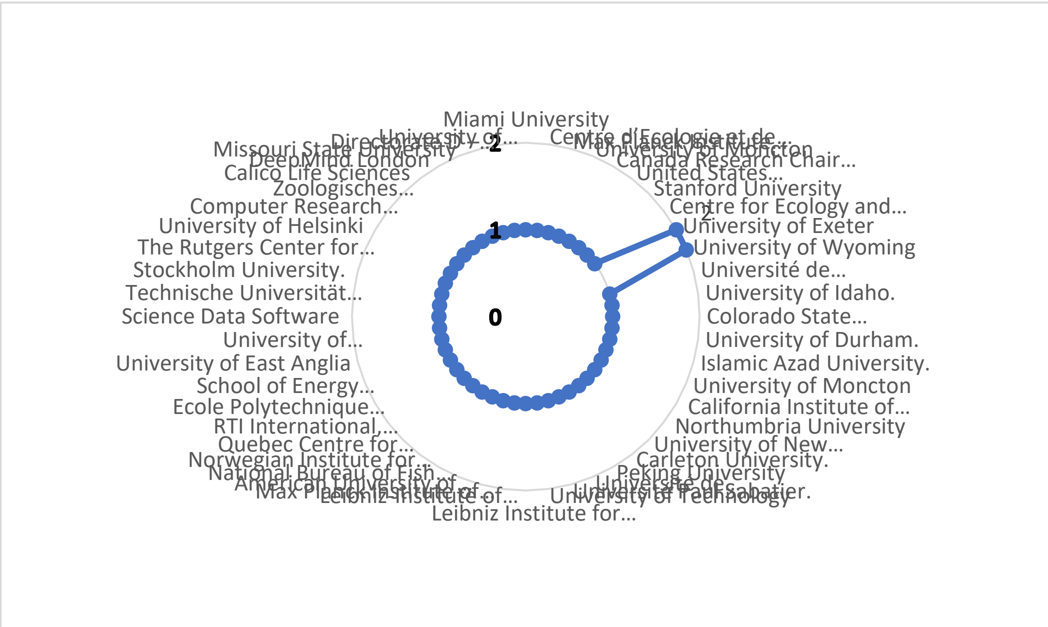
No	Ref	Citation	Objective	Data Subject	Method
			animal species in camera trap images to enhance ecological studies.	the United States and one in Canada, involving over 3.7 million images covering 27 species or groups.	the ResNet-18 architecture and testing the model on an independent subset of images for validation.
11	(Villéger et al., 2017)	400	Reviewing current functional ecology approaches to fish and identifying future challenges to enhance the conservation of ecosystem services provided by fish.	Fish communities in freshwater and marine ecosystems are facing anthropogenic pressures, increasing biodiversity loss, and threatening ecosystem services.	Literature study on fish functional attributes, meta-analysis on global change, functional diversity, and the relationship between fish community functional diversity and ecosystem services.
12	(Daw et al., 2015)	390	Exploring "taboo" trade-offs in ecosystem service management and human well-being through participatory modeling and narrative scenarios in tropical small-scale fisheries.	Key stakeholders in small-scale fisheries in Nyali, Mombasa, Kenya, include fishermen, male and female traders, and the surrounding community.	Focus group discussions, fisheries ecosystem modeling, participatory modeling, narrative scenarios, and impact analysis on the well-being of various stakeholder groups.
13	(Wäldchen & Mäder, 2018)	389	Providing a guide and review on applying machine learning, especially deep learning, for image-based species identification.	Deep learning methods, such as convolutional neural networks (CNN) applied to extensive image datasets, including digital natural history collections.	Literature review on the application of deep learning in image-based species identification, and analysis of available machine learning frameworks.
14	(Geiger et al., 2014)	384	Evaluating the accuracy of DNA barcoding for identifying freshwater fish species in biodiversity hotspots in the Mediterranean and its implications for conservation priorities.	526 freshwater fish species from 20 countries in the Mediterranean hotspot region, with DNA barcode data from 3,165 specimens.	Using distance-based clustering analysis and tree models to measure the accuracy of species identification based on DNA barcodes, and calculating Evolutionarily Distinct and Globally Endangered (EDGE) scores.
15	(Peng et al., 2017)	383	Investigating the object-part attention model (OPAM) for fine-grained image classification, integrating two levels of attention to enhance multi-view and multi-scale feature learning.	Datasets CUB-200-2011, Cars-196, Oxford-IIIT Pet, and Oxford-Flower-102 were used for fine-grained image classification experiments, covering various subcategories of birds, cars, pets, and flowers.	Using an object-part attention model consisting of object-level attention for object localization and part-level attention for discriminative part selection, without object or part annotation in the training and testing phase.
16	(Hohenlohe et al., 2021)	361	Developing and applying population genomics tools for wildlife conservation and management, focusing on population size, structure, and adaptive variation.	Wildlife populations such as wolves, tigers, pumas, red deer, and various bird species were sampled from diverse geographical locations to analyze genetic variation and adaptation.	Using advanced genomic sequencing techniques like RADseq, WGS, and genome-wide association studies (GWAS) to collect and analyze genetic data, and develop genetic marker panels for population management.
17	(Muneer, 2014)	327	Analyzing the impact of hybridization between native and invasive trout on the genetic diversity and survival of native trout populations.	Native and invasive trout populations in different aquatic habitats.	Collecting genetic data using microsatellite methods and demographic analysis to measure the level of hybridization and genetic variation.
18	(Korotcov et al., 2017)	335	Comparing the performance of deep learning with other machine learning methods using various drug discovery datasets.	Datasets on solubility, probe-likeness, hERG, KCNQ1, bubonic plague, Chagas disease, tuberculosis, and malaria.	Using a prediction pipeline with classical methods (Bernoulli Naive Bayes, logistic regression, AdaBoost decision tree, random forest, and SVM) and deep neural networks, with

No	Ref	Citation	Objective	Data Subject	Method
					evaluation using metrics such as AUC, F1 score, and others.
19	(Tuia et al., 2022)	332	Combining machine learning approaches with domain knowledge to improve ecological models and hybrid modeling tools.	Wildlife observed through modern sensors for animal ecology.	Cross-disciplinary collaboration combining affordable and accessible sensors with machine learning for large-scale data analysis.
20	(Boulent et al., 2019)	331	Synthesizing studies that use CNN for automatic plant disease identification from images and assessing its potential as an operational tool.	Studies using RGB images for automatic plant disease identification.	Literature survey through SCOPUS, reviewing 19 articles, analysis of study profiles, CNN implementation aspects, and performance.

Figure 2 below shows a diagram depicting various institutions involved in deep learning research. These institutions are represented as circles surrounding the center of the diagram, with institution names labeled around the edges of the circles. Some of the institutions listed include the University of Exeter, the University of Wyoming, Stanford University, and many others. This diagram may be used to illustrate the relationships or contributions of various institutions in deep learning research, with the size or position potentially indicating the level of involvement or influence of each institution.

Figure 2

Distribution of affiliations that conducted research



The distribution of publishers that have published articles on Deep Learning for fish identification is shown in Figure 3. Based on the figure, it can be seen that these articles are published by various publishers in varying numbers. Below is a more detailed description of these publishers:

1. Elsevier: Dominates with 164 articles, indicating that Elsevier is the largest publisher in this category.
2. Wiley Online Library: Ranks second with 107 articles, also serving as a significant source for this topic.

3. Springer: With 60 articles, it stands as another major publisher.
4. Nature.com: Contributes 36 articles, making it an important source in this research.
5. Frontiersin.org: Provides 31 articles, equal to the contribution from journals.plos.org, which also has 31 articles.
6. Books.google.com: Contributes 32 articles, indicating that books also serve as a relevant information source.
7. Academic.oup.com: Publishes 28 articles, making it one of the few major active publishers.
8. Mdpi.com: Provides 22 articles, highlighting its important role in related publications.
9. Cell.com: Has 19 articles, contributing substantially to this topic.
10. Ieeexplore.ieee.org: Provides 15 articles, showing the involvement of the engineering community in this research.
11. Taylor & Francis: Publishes 14 articles, making it a relevant publisher.
12. ACS Publications: Contributes several articles, though the specific number is not mentioned, providing valuable contributions to the scientific literature.
13. Am Soc Microbiology: Also contributes an unspecified number of articles, demonstrating the relevance of microbiology in this research.
14. Nations Academy of Sciences: Has several articles that provide important insights into this field.

In addition to these major publishers, there are various other publishers that contribute a smaller number of articles, such as Cornell University Press, CSIRO Publishing, datascienceassn.org, degruyter.com, dergipark.org.tr, dl.acm.org, elibrary.kdpu.edu.ua, and many others. This wide distribution of articles shows that research on Deep Learning for fish identification has received broad attention from leading publishers worldwide.

Figure 3

Publisher's article on deep learning for fish identification

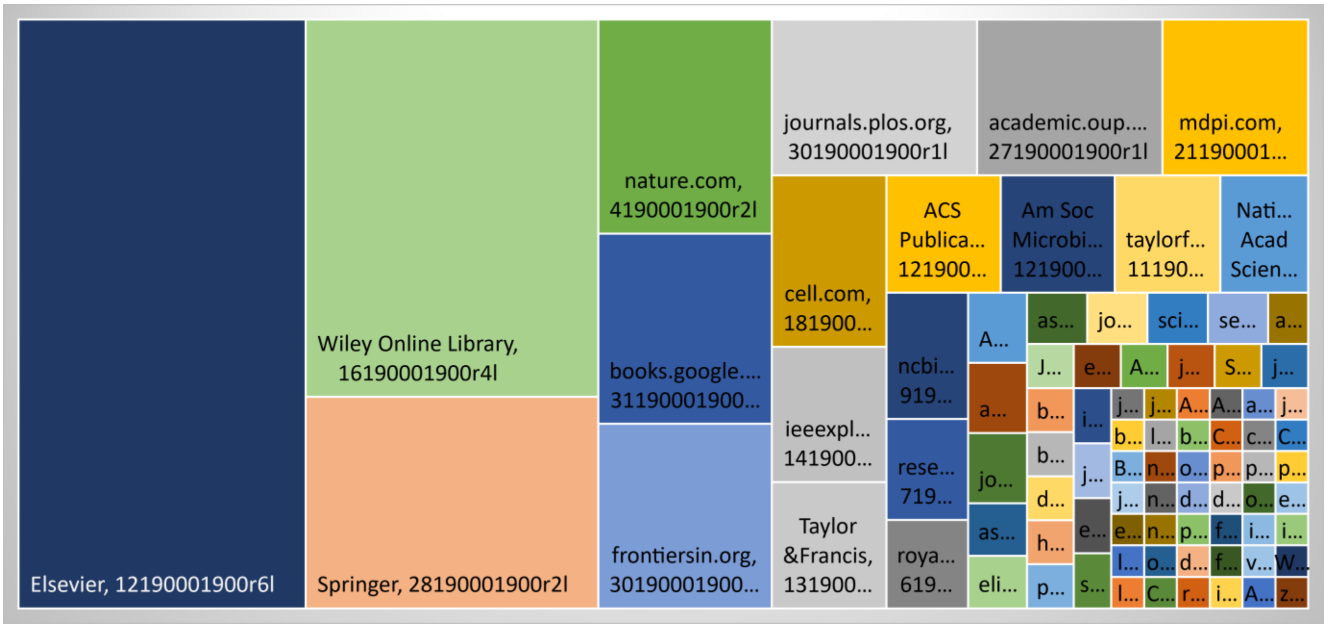


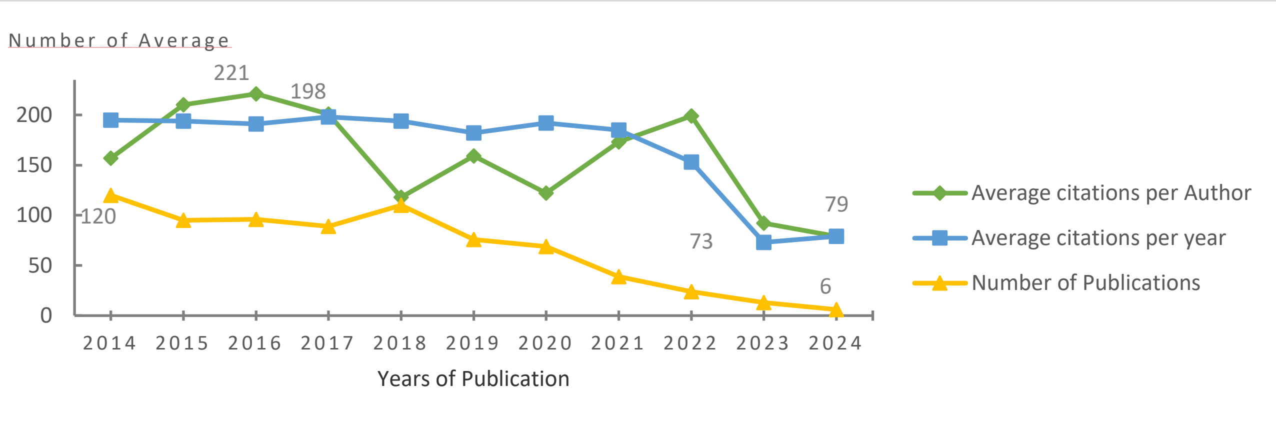
Figure 4 below illustrates the development of research in the field of deep learning published in journals indexed by Google Scholar, with a specific focus on fish identification, from 2014 to 2024. According to the data presented, a total of 737 articles were published during this period. The number of publications varied each year, starting with 120 publications in 2014 and peaking in 2017 with 221 publications. However, after 2017, there was a significant downward trend in the number of publications, dropping to just 6 publications in 2024. In addition to the number of publications, the graph also shows the average citations per year and average citations per author. The average citations per year remained relatively stable, ranging from 182 to 210 citations between 2014 and 2021, before experiencing a sharp decline thereafter. By 2024, the average citations per year had decreased to 79.

The average citations per author exhibited greater fluctuations. Initially, this figure was quite high, reaching 210 citations per author in 2016. However, it drastically declined in the subsequent years, with some notable peaks and troughs. For instance, the average citations per author rose again to 199 in 2020 but then sharply fell to 79 in 2024.

This data indicates that research on deep learning and fish identification remains relatively underexplored each year. Despite peaks in publication during certain years, the general trend shows a decline in both the number of studies and citations, which may suggest a decreasing interest or focus on this field in the last decade.

Figure 4

Graph of research progress on deep learning and fish identification



Computational mapping was conducted on article data, utilizing VOSviewer in the computational mapping process. The mapping results identified 91 items. Each item related to deep learning in fish identification within data mapping is divided into 9 clusters:

a. Cluster 1 contains 21 items and is marked in red. The keywords include biodiversity, environmental DNA, field, fish, fish examples, fish types, freshwater fish, importance, Indonesia, information, knowledge, marine, organisms, research, current research, researchers, species, taxonomic classification, taxonomy, tools, and vertebrates.

b. Cluster 2 consists of 16 items marked in green. The keywords include application, biodiversity, book, classification scheme, conservation, context, education, future, issues, learning, science, sharks, teaching, technology, training, and university.

c. Cluster 3 contains 14 items marked in blue. The keywords include algorithm, classification accuracy, data, deep learning, detection, fish consumption, fish schools, machine learning, neural network, pilot study, systems, tasks, and techniques.

d. Cluster 4 consists of 13 items marked in yellow. The keywords include artificial intelligence, biological functions, citizen science, current studies, development, experience, genes, identification, implications, project, skills, target, and teacher.

e. Cluster 5 contains 9 items marked in purple. The keywords include classification, ecology, field guide, fish investigation, fish stock, images, resources, species identification, and treatment.

f. Cluster 6 contains 8 items marked in light blue. The keywords include diversity, ecosystem services, fishing activities, indicators, population, research, researchers, and rivers.

g. Cluster 7 consists of 7 items marked in orange. The keywords include adolescents, comparative studies, effectiveness, environment, higher education, school, and students.

h. Cluster 8 contains 2 items marked in brown. The keywords include biology and focus.

i. Cluster 9 contains 1 item marked in white. The keywords include a classification system.

Table 1 shows that advances in sophisticated technology have significantly impacted various scientific fields. Havel et al. (2015) identified the challenges aquatic invasive species face in freshwater ecosystems, while Avsec et al. (2021) developed a deep learning model, Enformer, for predicting gene expression. La Notte et al. (2017) refined ecosystem service classifications with a systems ecology perspective, and Valletta et al. (2017) introduced machine learning methods for animal behavior data analysis. Neshat et al. (2014) reviewed AFSO algorithms in optimization, and Christin et al. (2019) explored deep learning applications in ecology. Ekins et al. (2019) enhanced drug discovery efficiency using machine learning, and Silva et al. (2018) provided a roadmap for fishway research. Port et al. (2016) used environmental DNA for biodiversity surveys, while Tabak et al. (2019) developed machine learning models for classifying animal species in camera trap images. Villéger et al. (2017) reviewed fish functional ecology approaches, and Daw et al. (2015) explored trade-offs in small-scale fishery ecosystem management. Wäldchen & Mäder (2018) guided the use of deep learning for image-based species identification, while Geiger et al. (2014) evaluated the accuracy of DNA barcoding for fish identification. Peng et al. (2017) examined object-part attention models for fine image classification, and Hohenlohe et al. (2021) developed genomic tools for wildlife conservation. Muneer (2014) analyzed the impact of trout hybridization, while Korotcov et al. (2017) compared deep learning performance in drug discovery. Tuia et al. (2022) combined machine learning with domain knowledge to improve ecological models, and Boulent et al. (2019) assessed the potential of CNN for plant disease identification.

These studies clearly demonstrate that advanced technologies, particularly machine learning and deep learning, have become essential tools in scientific research and the development of innovative solutions across various fields. Publications on deep learning for fish identification have drawn attention from leading publishers worldwide. These articles have been published by numerous publishers with varying distributions (Figure 3). The broad distribution of these articles indicates that research on deep learning for fish identification has garnered significant and widespread attention from various publishers globally, presenting a great opportunity for further research in deep learning and publication in diverse publishers.

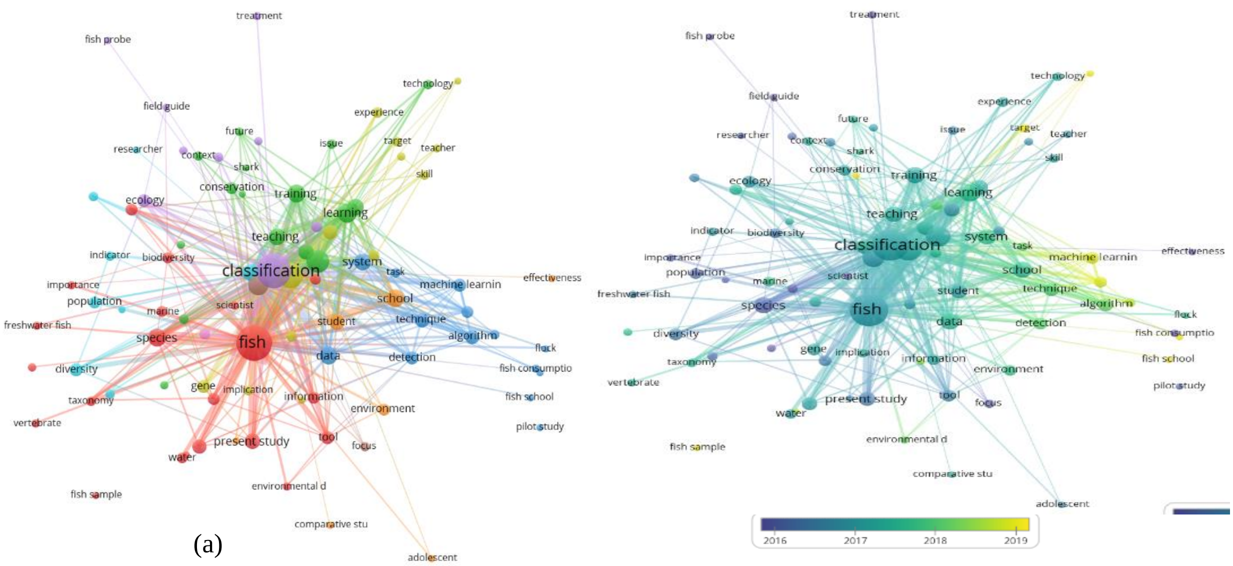
The visualization format of the VOSviewer application examines three aspects: network visualization, overlay visualization, and density visualization (see Figure 5). Each term is marked with a colored circle, and the size of the circle varies according to the frequency of the term (Nandiyanto & Al Husaeni, 2021). This visualization shows the relationships between terms on the map, represented by lines or networks connecting one term to another (NurFarahim et al., 2024).

The network visualization of the term "deep learning" for fish identification is presented in Figure 5. It can be seen that the terms "classification" and "fish" are positioned in the center with larger circle sizes, indicating that these two terms frequently appear and have a close relationship with other terms in the context of deep learning for fish identification. Figure 5 displays clusters for each frequently researched term related to the research theme. The clusters in the network visualization indicate that research on deep learning in fish identification can be divided into two domains, namely fish and classification.

The term fish belongs to cluster 1 with a total link strength of 554, link strength of 1644, and occurrence of 707, and the second term is classification, which belongs to cluster 5 with a total link strength of 232, link strength of 922, and occurrence of 410. The more frequently a term appears in the title and abstract, the larger the label circle size, indicating a positive correlation between circle size and term frequency (Sun et al., 2023; Xie et al., 2020).

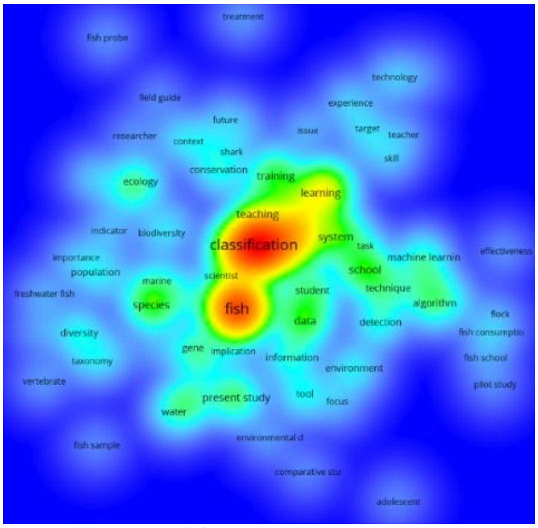
Figure 5

(a) Network Visualization, (b) Overlay Visualization, and (c) Density Visualization of Deep Learning and Fish Identification Keywords.



(a)

(b)



(c)

The overlay visualization from deep learning research for fish identification highlights the uniqueness of the study on related terms (Baker et al., 2020; Guo et al., 2019). Figure 3 shows that research on deep learning for fish identification was most frequently conducted between 2014 and 2018. The popularity period of the term deep learning for fish identification in research is relatively long.

Besides Network Visualization, VOSviewer supports overlay mapping as a type of visualization. Overlay Visualization emphasizes the assessment of the novelty of terms within the research context. Figure 3 depicts the novelty of terms in research related to deep learning for fish identification. In this type of term mapping, the popularity of terms over the years is illustrated. The colors in Overlay Visualization represent the novelty of terms during specific periods (Van Eck & Waltman, 2017; Moral-muñoz et al., 2020).

The research scope covers the period from 2014 to 2024. Darker colors, tending towards purple, indicate that research on a particular term was more frequent around 2016. Conversely, lighter colors, tending towards yellow, indicate that the term appeared more frequently in new research starting from 2019. Figure 3 shows an overlay visualization with deep learning and machine learning as the most searched research keywords. Other related terms include artificial intelligence, biological functions, citizen science, current studies, development, experience, genes, identification, implications, projects, skills, targets, and teachers. The overlay visualization effectively illustrates the evolution of research over time and the relationships between these terms. Thus, this mapping challenges further research on deep learning for fish identification.

Density Visualization maps research results based on brightness (Guo et al., 2019). More research has been conducted when the yellow hue is brighter, and the circle label diameter is larger (Muhuri et al., 2019). This indicates that much research related to these terms has been conducted. The labels of deep learning or machine learning in fish identification appear bright green. Conversely, if the color of the term fades towards the background color, then research on the term is rarely conducted (Donthu et al., 2021; Van Eck & Waltman, 2017). This suggests that these terms are frequently used in existing research. Density visualization analysis of all fish identification articles from 2014 to 2024 indicates that research related to terms such as classification, fish, learning, genes, systems, techniques, schools, species, algorithms, data, learners, and training has high research volumes. These results confirm the effectiveness of bibliometric analysis in exploring and visualizing current literature, providing a basis for deciding on further research needs.

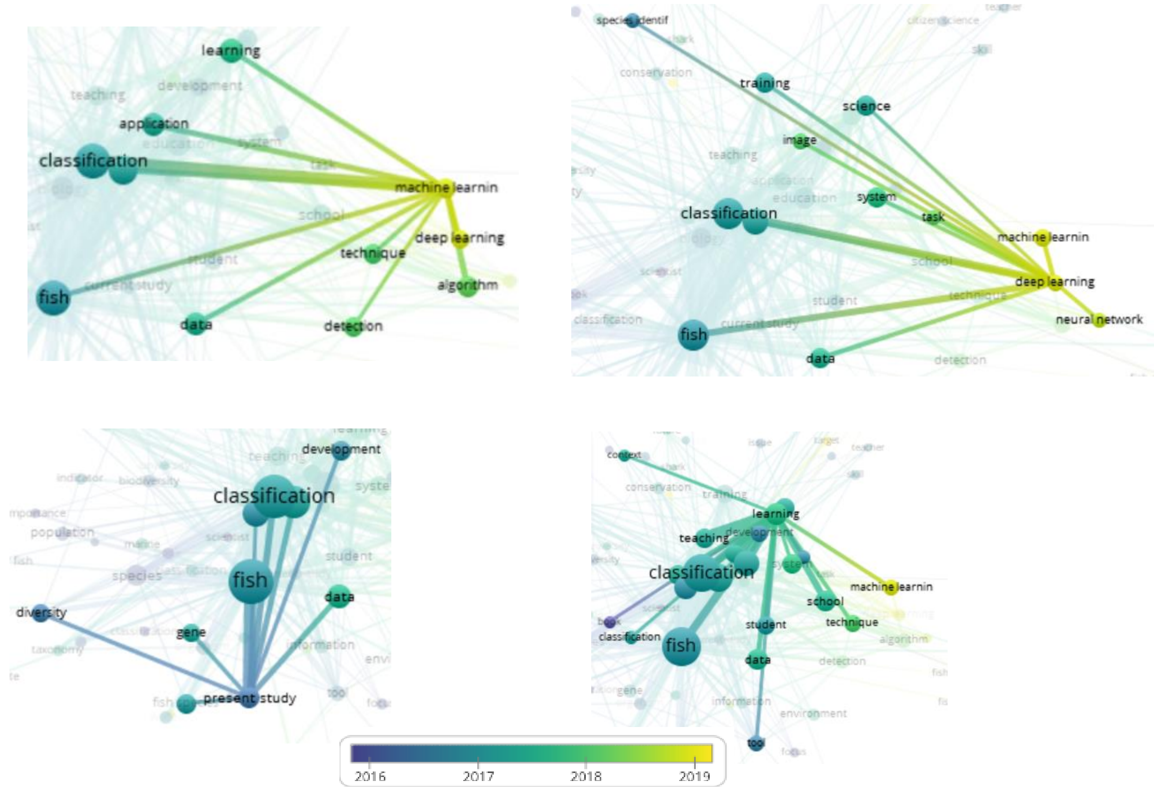
Network Visualization of the relationship between deep learning and other terms from all fish identification articles from 2014-2024 shows connections with terms such as classification, fish, application, detection, neural networks, tasks, images, learning, systems, techniques, species identification, algorithms, data, diversity, current research, genes, learning, schools, context, and training. Data shows that deep learning in fish identification is still rarely associated with other terms. Based on the results, deep learning in fish identification is connected to 58 terms, with a total link strength of 147 and an occurrence of 48. Other studies have shown that morphological and genomic identification of fish is highly needed for conservation efforts and to determine their kinship level (Young et al., 2019).

4. DISCUSSION

Based on visualization results using VOSviewer, it is assumed that the field of deep learning in fish identification is still highly researchable and can be connected with other terms. This will have a greater influence on the novelty of research. Based on the article data mapping, it is observed that the keyword deep learning is trending in research. Based on this study, new research on deep learning can be explored.

Figure 6

Visualization of deep learning network with other terms



Integrating advanced fish identification technology with a comprehensive educational approach is crucial for promoting sustainability. By addressing both technical challenges and educational aspects, we can enhance marine biodiversity management and improve students' understanding of ecological relationships, ultimately contributing to more sustainable practices and policies. This aligns with the findings of Echeverria et al., (2021), Hitchcock et al., (2021), and Unger et al., (2021) which shows that the use of new technologies, including artificial intelligence-based platforms like iNaturalist, increases students' biological literacy through direct observation and community-based species identification.

Many students perceive species identification as mere rote learning, which can diminish its perceived value (Palmberg et al., 2015; Palmberg et al., 2018; Palmberg et al., 2019). However, comprehensive species identification education, which includes understanding organism characteristics, systematic groups, and their roles in ecosystems, is essential for fostering a deeper appreciation of biodiversity and sustainability (Duerden & Witt, 2010; Lindemann-Matthies & Bose, 2008; Randler & Heil, 2021). Educational programs that combine nature experiences and outdoor learning can significantly enhance students' environmental knowledge, attitudes, and behaviors, promoting a more ecocentric worldview (Cheng & Monroe, 2012). These experiences not only build confidence in teaching biodiversity but also foster emotional connections with nature, which are vital for effective sustainability education (Brundiers & Wiek, 2017; Quinn et al., 2016).

These findings indicate that research on deep learning in fish identification has significant potential to be integrated into biodiversity education to enhance learner engagement and learning experiences. This bibliometric analysis relies entirely on the Google Scholar database. Moreover, only search phrases (such as "Deep Learning" or "Fish Identification") were used to generate sample articles for the study. Other databases and keywords still exist. We acknowledge that results may vary depending on the database (e.g., Scopus and Web of Science) and other search phrases used. Some highly cited works were published in journals that did not include author keywords. To illustrate the keyword network, we analyzed only articles with available author keywords. In this analysis, the most cited publications were identified using criteria of more than 100 citations.

5. CONCLUSION

The computational mapping analysis of bibliometric data on research articles themed “deep learning for fish identification” identified 737 relevant articles published between 2014 and 2024. The articles were sourced from the Google Scholar database using the Publish or Perish tool, with bibliographic data including titles and abstracts. This study generated nine clusters that depict the relationships between key terms frequently appearing in deep learning and fish identification research. Overall, the data indicate that research on deep learning and fish identification has been relatively infrequent each year. Despite peaks in publication during certain years, the general trend shows a decline in the number of studies and citations, which may suggest a decreasing interest or focus on this field over the past decade.

The network visualization of the relationship between deep learning and other terms still provides opportunities for further exploration. Other related terms include: gene/genome, classification, fish, application, detection, neural network, task, image, learning, system, technique, species identification, algorithm, data, diversity, current research, education, context, and training. These findings indicate that despite the observed decline, there are still significant research opportunities in the field of deep learning for fish identification, which is interconnected with various other aspects. The integration of deep learning in fish identification offers significant opportunities in biodiversity education. This technology not only enhances students' analytical skills but also fosters interest and appreciation for nature. Thus, this approach can contribute to more effective and relevant sustainability education.

For future research, it is recommended to conduct a broader literature mapping by systematically searching academic databases such as Scopus and Web of Science. This approach can help identify emerging trends, gaps, and potential directions in the study of flourishing, well-being, and positive psychology. Additionally, further studies could explore the applicability of the Flourishing Scale PERMA across diverse populations, educational contexts, and cultural settings, as well as examine additional constructs, such as resilience, that may enhance the comprehensive measurement of well-being.

Ethical Approval: The study adheres to the ethical guidelines for conducting research.

Conflict of Interest: The authors declare no conflict of interest in this work.

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Ethical Approval: The study adheres to the ethical guidelines for conducting research.

REFERENCES

Avsec, Ž., Agarwal, V., Visentin, D., Ledsam, J. R., Grabska-Barwinska, A., Taylor, K. R., ... & Kelley, D. R. (2021). Effective gene expression prediction from sequence by integrating long-range interactions. *Nature Methods*, *18*(10), 1196-1203. https://www.nature.com/articles/s41592-021-01252-x

Baker, H. K., Pandey, N., Kumar, S., & Haldar, A. (2020). A bibliometric analysis of board diversity: Current status, development, and future research directions. *Journal of Business Research*, *108*, 232-246. https://www.sciencedirect.com/science/article/pii/S0148296319306976

Ben Tamou, A., Benzinou, A., & Nasreddine, K. (2022). Targeted data augmentation and hierarchical classification with deep learning for fish species identification in underwater images. *Journal of Imaging*, *8*(8), 214. https://www.mdpi.com/2313-433X/8/8/214

Boulent, J., Foucher, S., Théau, J., & St-Charles, P. L. (2019). Convolutional neural networks for the automatic identification of plant diseases. *Frontiers in Plant Science*, *10*, 941. https://www.frontiersin.org/journals/plant-science/articles/10.3389/fpls.2019.00941/full

Brundiers, K., & Wiek, A. (2017). Beyond interpersonal competence: Teaching and learning professional skills in sustainability. *Education Sciences*, *7*(1), 39. https://www.mdpi.com/2227-7102/7/1/39

Cheng, J. C. H., & Monroe, M. C. (2012). Connection to nature: Children's affective attitude toward nature. *Environment and behavior*, *44*(1), 31-49. https://journals.sagepub.com/doi/abs/10.1177/0013916510385082

Christin, S., Hervet, É., & Lecomte, N. (2019). Applications for deep learning in ecology. *Methods in Ecology and Evolution*, *10*(10), 1632-1644. https://besjournals.onlinelibrary.wiley.com/doi/abs/10.1111/2041-210X.13256

Daw, T. M., Coulthard, S., Cheung, W. W., Brown, K., Abunge, C., Galafassi, D., ... & Munyi, L. (2015). Evaluating taboo trade-offs in ecosystem services and human well-being. *Proceedings of the National Academy of Sciences*, *112*(22), 6949-6954. https://www.pnas.org/doi/abs/10.1073/pnas.1414900112

Donthu, N., Kumar, S., Mukherjee, D., Pandey, N., & Lim, W. M. (2021). How to conduct a bibliometric analysis: An overview and guidelines. *Journal of Business Research*, *133*, 285-296. https://www.sciencedirect.com/science/article/pii/S0148296321003155

Duerden, M. D., & Witt, P. A. (2010). The impact of direct and indirect experiences on the development of environmental knowledge, attitudes, and behavior. *Journal of Environmental Psychology*, *30*(4), 379-392. https://www.sciencedirect.com/science/article/pii/S0272494410000344

Echeverria, A., Ariz, I., Moreno, J., Peralta, J., & Gonzalez, E. M. (2021). Learning plant biodiversity in nature: The use of the citizen–science platform iNaturalist as a collaborative tool in secondary education. *Sustainability*, *13*(2), 735. https://www.mdpi.com/2071-1050/13/2/735

Ekins, S., Puhl, A. C., Zorn, K. M., Lane, T. R., Russo, D. P., Klein, J. J., ... & Clark, A. M. (2019). Exploiting machine learning for end-to-end drug discovery and development. *Nature Materials*, *18*(5), 435-441. https://www.nature.com/articles/s41563-019-0338-z

Geiger, M. F., Herder, F., Monaghan, M. T., Almada, V., Barbieri, R., Bariche, M., ... & Freyhof, J. (2014). Spatial heterogeneity in the Mediterranean Biodiversity Hotspot affects barcoding accuracy of its freshwater fishes. *Molecular ecology resources*, *14*(6), 1210-1221. https://onlinelibrary.wiley.com/doi/abs/10.1111/1755-0998.12257

Guo, Y. M., Huang, Z. L., Guo, J., Li, H., Guo, X. R., & Nkeli, M. J. (2019). Bibliometric analysis on smart cities research. *Sustainability*, *11*(13), 3606. https://www.mdpi.com/2071-1050/11/13/3606

Havel, J. E., Kovalenko, K. E., Thomaz, S. M., Amalfitano, S., & Kats, L. B. (2015). Aquatic invasive species: challenges for the future. *Hydrobiologia*, *750*(1), 147-170. https://link.springer.com/article/10.1007/s10750-014-2166-0

Hindarto, D. (2023). Comparative analysis vgg16 vs mobilenet performance for fish identification. *International Journal of Software Engineering and Computer Science (IJSECS)*, *3*(3), 270-280.

Hitchcock, C., Sullivan, J., & O'Donnell, K. (2021). Cultivating bioliteracy, biodiscovery, data literacy, and ecological monitoring in undergraduate courses with iNaturalist. https://researcharchive.lincoln.ac.nz/items/3471f3c6-f7a7-4937-9150-03bd3c00691c

Hohenlohe, P. A., Funk, W. C., & Rajora, O. P. (2021). Population genomics for wildlife conservation and management. *Molecular ecology*, *30*(1), 62-82. https://onlinelibrary.wiley.com/doi/abs/10.1111/mec.15720

Iwahara, Y., Shibata, Y., Manano, M., Nishino, T., Kariya, R., & Yaemori, H. (2024). Effects of input image size on the accuracy of fish identification using deep learning. *bioRxiv*, 2024-03. https://www.biorxiv.org/content/10.1101/2024.03.01.582886.abstract

Korotcov, A., Tkachenko, V., Russo, D. P., & Ekins, S. (2017). Comparison of deep learning with multiple machine learning methods and metrics using diverse drug discovery data sets. *Molecular pharmaceutics*, *14*(12), 4462-4475. https://pubs.acs.org/doi/abs/10.1021/acs.molpharmaceut.7b00578

La Notte, A., d'AMATO, D., Mäkinen, H., Paracchini, M. L., Liquete, C., Egoh, B., ... & Crossman, N. D. (2017). Ecosystem services classification: A systems ecology perspective of the cascade framework. *Ecological indicators*, *74*, 392-402. https://www.sciencedirect.com/science/article/pii/S1470160X16306677

Lindemann-Matthies, P., & Bose, E. (2008). How many species are there? Public understanding and awareness of biodiversity in Switzerland. *Human ecology*, *36*(5), 731-742. https://link.springer.com/article/10.1007/s10745-008-9194-1

Mohammadisabet, A., Hasan, R., Dattana, V., Mahmood, S., & Hussain, S. (2025). CNN-based optimization for fish species classification: Tackling environmental variability, class imbalance, and real-time constraints. *Information*, *16*(2), 154. https://www.mdpi.com/2078-2489/16/2/154

Moral Muñoz, J. A., Herrera-Viedma, E., Santisteban Espejo, A. L., & Cobo Martín, M. J. (2020). Software tools for conducting bibliometric analysis in science: An up-to-date review. https://rodin.uca.es/handle/10498/22857

Muhuri, P. K., Shukla, A. K., & Abraham, A. (2019). Industry 4.0: A bibliometric analysis and detailed overview. *Engineering applications of artificial intelligence*, *78*, 218-235. https://www.sciencedirect.com/science/article/pii/S0952197618302458

Muneer, P. A. (2014). Application of microsatellite markers in conservation genetics and fisheries management: recent advances in population structure analysis and conservation strategies. *Genetics Research International*, *2014*(1), 691759. https://onlinelibrary.wiley.com/doi/abs/10.1155/2014/691759

Nandiyanto, A. B. D., & Al Husaeni, D. F. (2021). A bibliometric analysis of materials research in an Indonesian journal using VOSviewer. *Journal of Engineering Research*. https://kuwaitjournals.org/jer/index.php/JER/article/view/16037

Neshat, M., Sepidnam, G., Sargolzaei, M., & Toosi, A. N. (2014). Artificial fish swarm algorithm: a survey of the state-of-the-art, hybridization, combinatorial, and indicative applications. *Artificial intelligence review*, *42*(4), 965-997. https://link.springer.com/article/10.1007/s10462-012-9342-2

NurFarahim, S., Shabil, A., & Balqis, N. S. (2024). Deep Learning for Sea Turtle Classification: A Bibliometric Analysis Using VOSviewer. *International Journal of Informatics, Information System and Computer Engineering (INJIISCOM)*, *5*(1), 88-101. https://ojs.unikom.ac.id/index.php/injiiscom/article/view/12487

Palmberg, I., Berg, I., Jeronen, E., Kärkkäinen, S., Norrgård-Sillanpää, P., Persson, C., ... & Yli-Panula, E. (2015). Nordic–Baltic student teachers' identification of and interest in plant and animal species: The importance of species identification and biodiversity for sustainable development. *Journal of Science Teacher Education*, *26*(6), 549-571. https://link.springer.com/article/10.1007/s10972-015-9438-z

Palmberg, I., Hermans, M., Jeronen, E., Kärkkäinen, S., Persson, C., & Yli-Panula, E. (2018). Nordic student teachers' views on the importance of species and species identification. *Journal of Science Teacher Education*, *29*(5), 397-419. https://www.tandfonline.com/doi/abs/10.1080/1046560X.2018.1468167

Palmberg, I., Kärkkäinen, S., Jeronen, E., Yli-Panula, E., & Persson, C. (2019). Nordic student teachers' views on the most efficient teaching and learning methods for species and species identification. *Sustainability*, *11*(19), 5231. https://www.mdpi.com/2071-1050/11/19/5231

Peng, Y., He, X., & Zhao, J. (2017). Object-part attention model for fine-grained image classification. *IEEE Transactions on Image Processing*, *27*(3), 1487-1500. https://ieeexplore.ieee.org/abstract/document/8110709/

Port, J. A., O'Donnell, J. L., Romero-Maraccini, O. C., Leary, P. R., Litvin, S. Y., Nickols, K. J., ... & Kelly, R. P. (2016). Assessing vertebrate biodiversity in a kelp forest ecosystem using environmental DNA. *Molecular ecology*, *25*(2), 527-541. https://onlinelibrary.wiley.com/doi/abs/10.1111/mec.13481

Quinn, F., Castéra, J., & Clément, P. (2016). Teachers' conceptions of the environment: Anthropocentrism, non-anthropocentrism, anthropomorphism and the place of nature. *Environmental Education Research*, *22*(6), 893-917. https://www.tandfonline.com/doi/abs/10.1080/13504622.2015.1076767

Randler, C., & Heil, F. (2021). Determinants of bird species literacy—activity/interest and specialization are more important than socio-demographic variables. *Animals*, *11*(6), 1595. https://www.mdpi.com/2076-2615/11/6/1595

Robillard, A. J., Trizna, M. G., Ruiz-Tafur, M., Dávila Panduro, E. L., de Santana, C. D., White, A. E., ... & Deichmann, J. L. (2023). Application of a deep learning image classifier for the identification of Amazonian fishes. *Ecology and Evolution*, *13*(5), e9987. https://onlinelibrary.wiley.com/doi/abs/10.1002/ece3.9987

Silva, A. T., Lucas, M. C., Castro-Santos, T., Katopodis, C., Baumgartner, L. J., Thiem, J. D., ... & Cooke, S. J. (2018). The future of fish passage science, engineering, and practice. *Fish and Fisheries*, *19*(2), 340-362. https://onlinelibrary.wiley.com/doi/abs/10.1111/faf.12258

Siri, D., Vellaturi, G., Ibrahim, S. H. S., Molugu, S., Desanamukula, V. S., Kocherla, R., & Vatambeti, R. (2024). Enhanced deep learning models for automatic fish species identification in underwater imagery. *Heliyon*, *10*(15). https://www.cell.com/heliyon/fulltext/S2405-8440(24)11248-0

Sun, H., Wang, Z., Wang, Y., Rong, H., Wang, D., Liu, X., ... & Fan, Q. (2023). Bibliometric and visualized analysis of sodium–glucose cotransporter 2 inhibitors. *Frontiers in Pharmacology*, *13*, 1009025. https://www.frontiersin.org/journals/pharmacology/articles/10.3389/fphar.2022.1009025/full

Tabak, M. A., Norouzzadeh, M. S., Wolfson, D. W., Sweeney, S. J., VerCauteren, K. C., Snow, N. P., ... & Miller, R. S. (2019). Machine learning to classify animal species in camera trap images: Applications in ecology. *Methods in Ecology and Evolution*, *10*(4), 585-590. https://besjournals.onlinelibrary.wiley.com/doi/abs/10.1111/2041-210X.13120

Terefe, Z. A., Emiru, E. D., & Tassie, T. (2025). Identification of Indigenous fish species in Lake Tana using deep learning. *Scientific Reports*. https://www.nature.com/articles/s41598-025-29455-8

Tuia, D., Kellenberger, B., Beery, S., Costelloe, B. R., Zuffi, S., Risse, B., ... & Berger-Wolf, T. (2022). Perspectives in machine learning for wildlife conservation. *Nature communications*, *13*(1), 792. https://www.nature.com/articles/s41467-022-27980-y

Unger, S., Rollins, M., Tietz, A., & Dumais, H. (2021). iNaturalist as an engaging tool for identifying organisms in outdoor activities. *Journal of Biological Education*, *55*(5), 537-547. https://www.tandfonline.com/doi/abs/10.1080/00219266.2020.1739114

Valletta, J. J., Torney, C., Kings, M., Thornton, A., & Madden, J. (2017). Applications of machine learning in animal behaviour studies. *Animal Behaviour*, *124*, 203-220. https://www.sciencedirect.com/science/article/pii/S0003347216303360

Van Eck, N. J., & Waltman, L. (2017). Citation-based clustering of publications using CitNetExplorer and VOSviewer. *Scientometrics*, *111*(2), 1053-1070. https://link.springer.com/article/10.1007/s11192-017-2300-7

Villéger, S., Brosse, S., Mouchet, M., Mouillot, D., & Vanni, M. J. (2017). Functional ecology of fish: current approaches and future challenges. *Aquatic Sciences*, *79*(4), 783-801. https://link.springer.com/article/10.1007/s00027-017-0546-z

Wäldchen, J., & Mäder, P. (2018). Machine learning for image-based species identification. *Methods in Ecology and Evolution*, *9*(11), 2216-2225. https://besjournals.onlinelibrary.wiley.com/doi/abs/10.1111/2041-210X.13075

Xie, L., Chen, Z., Wang, H., Zheng, C., & Jiang, J. (2020). Bibliometric and visualized analysis of scientific publications on atlantoaxial spine surgery based on Web of Science and VOSviewer. *World Neurosurgery*, *137*, 435-442. https://www.sciencedirect.com/science/article/pii/S1878875020301893

Young, M. R., Moraza, M. L., Ueckermann, E., Heylen, D., Baardsen, L. F., Lima-Barbero, J. F., ... & Palevsky, E. (2019). Linking morphological and molecular taxonomy for the identification of poultry house, soil, and nest-dwelling mites in the Western Palearctic. *Scientific Reports*, *9*(1), 5784. https://www.nature.com/articles/s41598-019-41958-9

Zhang, J., & Wang, Y. (2024). A new workflow for instance segmentation of fish with YOLO. *Journal of Marine Science and Engineering*, *12*(6), 1010. https://www.mdpi.com/2077-1312/12/6/1010