Automatic wildlife species identification on camera trap images using deep learning approaches: a systematic review

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Article Info

Article history:

Received Nov 28, 2024
Revised Jul 29, 2025
Accepted Oct 14, 2025

Keywords:

Camera trap images
Deep learning
Image classification
Species identification
Wildlife animals

ABSTRACT

The foundation of systematic research depends on precise species identification, functioning as a critical component in the processes of biological research. Wildlife biologists are prompting for more effective techniques to fulfill the expanding need for species identification. The rise in open source image data showing animal species, captured by digital cameras and other digital methods of collecting data, has been monumental. This rapid expansion of animal image data, integrated with state-of-the-art machine learning techniques such as deep learning which has shown significant capabilities for automating species identification. This paper focuses on the role of deep neural network architectures in furthering technological advancements in automating species identification in recent years. To advocate further investigation in this field, an examination of machine learning architectures for species identification was presented in this work. This examination focuses primarily on image analyses and discusses their significance in wildlife conservation. Fundamentally, the aim of this article is to offer insights into the present advancements in automating species identification and to act as a reference for scholars who are keen to integrate machine learning techniques into ecological studies. Systems designed through Artificial Intelligence are extensive in providing toolkits for systematic identification of species in the upcoming years.

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1. INTRODUCTION

Biodiversity, which encompasses the variety of life forms on earth at different levels ranging from genetics to ecosystems, entails the evolutionary, ecological, and cultural elements that support life in diverse manifestations [1], [2]. It promotes ecological processes that lay the groundwork for essential ecosystem services, including the provision of food, water, maintenance of soil fertility, and control of pests and illnesses [3]. As a result, biodiversity conservation is essential for the coexistence of people and the survival of other living organisms within the ecosystem. Precise species identification serves as a foundation for all factors of systematic evaluation [1] and plays a decisive role in several biological research fields, including agricultural, ecology, and medicine studies. Extensive research efforts conducted in the domain of computer vision and machine learning have generated numerous publications proposing and evaluating automated species identification techniques [4], [5].

This work reviews scholarly sources that were undertaken to provide a comprehensive overview of the current state of knowledge. This review allows for the identification of relevant hypotheses, approaches, and research gaps within the existing body of literature. Additionally, it involves the application of proposed methodologies and scientific insights, presenting evidence to support theories and justifications, with the goal of establishing the validity of the study's findings. The study aims to respond to the concern of processing large amounts of imagery data to classify animals as an effort to assess biodiversity monitoring [6]. This work seeks to contribute to this expanding realm of academic literature.

A review of recent literature indicates that significant research has been conducted on using deep learning methods for automated species identification. However, the focus of this survey is primarily on the role of deep learning for animal species identification. Fundamentally, the growing interest in monitoring wildlife biodiversity or population monitoring essentially for maintaining ecological balance, protecting endangered species, and ensuring long-term sustainability for South Africa's biodiversity and natural resources [7].

Moreover, this will minimise the dangers that lie with ecological imbalances, as it will be help in avoiding human-wildlife conflict and overpopulation of some species or depletion of food resources. By implementing an effective monitoring system, conservationists and authorities can make informed decisions regarding habitat protection, population control measures, and conflict resolution strategies. In addition, the management of animal species guarantees the monitoring and equilibrium of species within the ecosystem.

2. RELATED WORK

Camera trap images are images captured by motion-sensor cameras, or "camera-traps", in wild habitats, and have revolutionised wildlife ecology and conservation [6]. Pardo, *et al.* [8] have studied 31 areas in South Africa with the aid of the Snapshot Safari – South Africa network; 21 of these areas are permanent grids for continuous monitoring. Camera traps are essential for wildlife conservation in South Africa, as they enable researchers and conservationists to gather important data on the presence, abundance, and behaviour of species in their natural habitats [9], [10].

Machine learning (ML), a subset of artificial intelligence (AI), can accomplish tasks without explicit programming for the related solution [11], [12]. Alternatively, it gains knowledge from prior instances of the same task through a series of processes referred to as training. Subsequently, ML can apply this gained knowledge to new data samples, a phase called inference [13]. ML is particularly beneficial for tasks requiring extraction of information from enormous and continually expanding datasets, making it well-equipped for scenarios where extant traditional analytical modelling faces difficulties, such as when performing analysis on visual material such as imagery and video data.

Computer vision (CV) is a discipline within computer science that focuses on collecting information from images and videos [14]-[16]. In the engineering domain, its aim is to automate operations analogous to those performed by human visual system [17]. As a result, CV primarily involves creating artificial systems designed to address specific visual challenges, and as such it employs techniques related to image processing and analysis [14]. Moreover, it is closely related to other fields such as machine learning and image recognition.

Deep learning is an expansion of frequently used ANNs, which are mathematical models influenced by the learning algorithms observed in biological neural networks, such as the central nervous system found in animals, specifically their brains. As a reference, the human brain typically consists of around 86 billion neurons [18]. The biological nervous system consists of a complex network that is made up of numerous neurons. Similarly, neurons serve as the fundamental processing components within artificial neural networks. With machine learning algorithms created with the purpose of identifying patterns within data for predictive ambitions, neural networks serve a similar role but with a higher level of complexity. The term "neural network" draws its inspiration from the similarity to the human brain, given its functional resemblance to the fundamental unit of the brain, the neuron [19]. In contrast to a biological brain, where neurons form connections with any other neuron within a particular physical range, ANNs are comprised of a fixed and predefined number of layers and connections. Neural networks are made up of several layers of interconnected neurons [20]. The type of neural network commonly used for deep learning in image processing is the convolutional neural network (CNN). Convolutional neural networks (CNNs) present a category of neural networks mainly recognised for their efficiency in handling image and video data [18].

3. MATERIALS AND METHODS

The basis of the research methodology is grounded based on a comprehensive review of the knowledge body using a systematic approach. This article follows a methodology defined by Kitchenham, *et al.* [21], the paper navigates a purposeful literature review. The motivation behind for a systematic review for automatic species identification using deep learning methods is that there is a steady deep learning intervention in wildlife conservation, as well as the applications and limitations. In addition, this methodology promotes the gathering, evaluation, analysis, and investigation of various methods in constructing a deep learning model, with the aim of identifying species in camera trap images. The first stage of this method is to formulate the research hypothesis of the paper. Table 1 shows the research questions for the hypothesis and motivation corresponding to the questions.

Table 1. Research question hypothesis and motivation corresponding to each question

Research question number	Research hypothesis	Motivation
1	What is the importance of ecological monitoring for wildlife conservation?	This question is to this is to assist in gaining a perspective of ecological monitoring. This will help understand the importance and ensuring the sustainability of wildlife, making a gateway to developing a system that will guarantee monitoring of animal species.
2	What are the camera trap images?	To address research question 2, a thorough search of what camera traps are and what role they play in helping wildlife monitoring will be done. In addition, this will highlight the challenges in processing image data using traditional methods.
3	What are the uses of machine learning in the field of computer vision?	In research question 3, an investigation on the integration of machine learning in the expanding field of computer vision will be conducted. This was to get insights of the necessity of these mechanisms in processing large amounts of data and look at the research done using these techniques.
4	What is deep learning?	In research question 4, a survey will be on what deep learning entails and the methods that make it stand out for recent advancements of image processing. A further investigation was done on the Convolutional Neural Networks and the success they brought to address related challenges.
5	What is the significance of deep learning methods for wildlife conservation?	The last research question focuses on reviewing the significance deep learning in wildlife conservation over the last few years.

3.1. Research hypothesis

The formulated research hypothesis for the paper was as follows:
Research Question 1: What is the importance of ecological monitoring for wildlife conservation?
Research Question 2: What are the camera trap images?
Research Question 3: What are the uses of machine learning in the field of computer vision?
Research Question 4: What is deep learning?
Research Question 5: What is the significance of deep learning methods for wildlife conservation?

3.2. Research strategy

The research strategy employed in this work involves a precise examination of various databases and journals. The majority of the papers were sourced from platforms such as IEEE Xplore, Science Direct, arXiv, Google Scholar, and Springer. After selecting the most relevant research repositories, key terms derived from the hypothesis were used to perform searches across relevant topics and altered versions of articles and papers. To enhance the precision of the search, a Boolean method was employed to assemble the essential search terminologies, resulting in the identification of a substantial number of peer-reviewed materials for this paper. During the application of search terminologies, considerations such as synonyms and multiple phrases were considered.

Table 2 details the search terminologies employed across different databases and the corresponding output. Initially, 218 papers were identified in the preliminary search. Subsequently, 25 redundant papers were discarded. This led to a total of 193 papers left. The remaining papers underwent refinement, and the final decision adhered to the standard set by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) Statement [22]. The PRISMA flowchart, as illustrated in Figure 1, outlines the screening process leading to the inclusion of literature in this paper.

3.3. Inclusion and exclusion guidelines

The guidelines for inclusion and exclusion were carefully selected as the criterion for assessing the formal writing standards within the scope of this paper. Based on these criteria, papers that aligned with the specified research outlook standard were considered for inclusion in the research scope. Details of the inclusion and exclusion guidelines are presented in Table 3.

Table 2. Terminologies across various databases

Database	Search Phrase	Results count
Springer	("Species identification") and ("species counting") using ("Machine learning") and ("deep learning")	23
Google Scholar	("Species identification") and (animal counting") using ("Machine learning") and ("deep learning")	134
Science Direct	("Species identification") and ("counting") using ("Machine learning") and ("deep learning")	51
IEEE Xplore	“Animal species identification using machine learning”	9
arXiv	“Species identification and counting using machine learning”	1

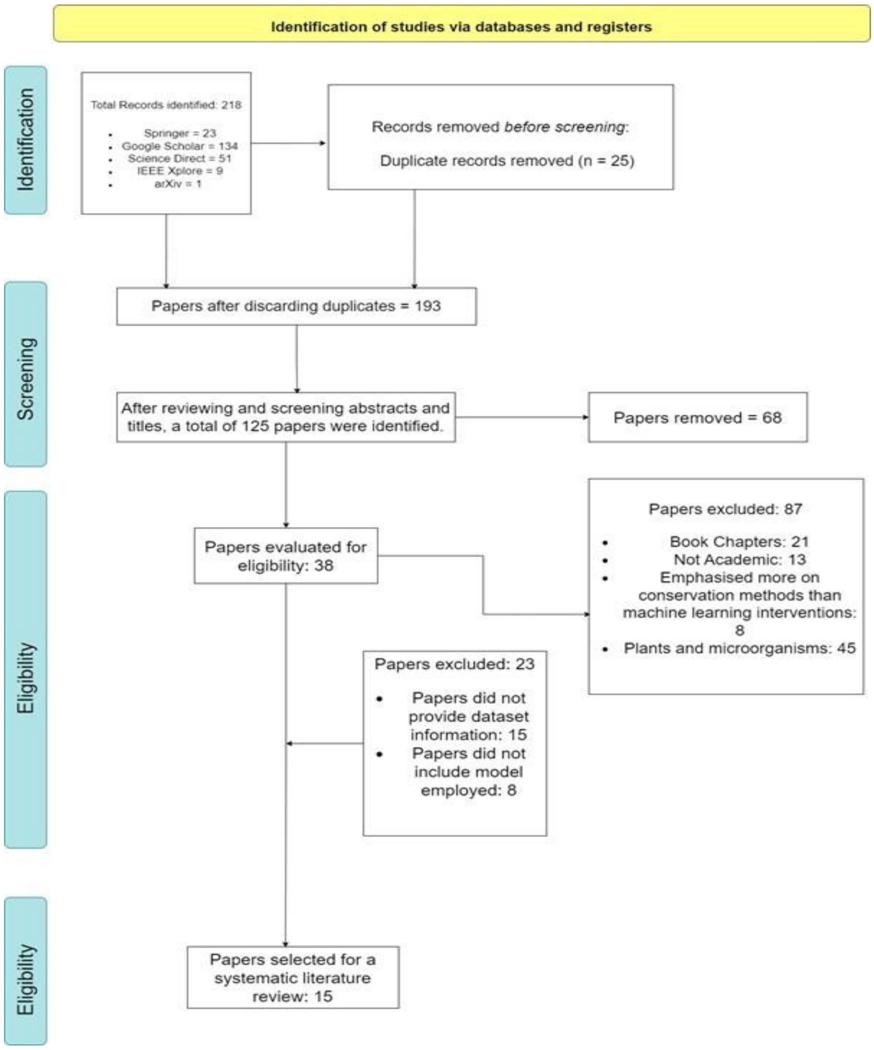

Figure 1. Flow diagram of paper selection

Table 3. Selected inclusion and exclusion guidelines

Inclusion	Exclusion
• The content must comprise peer-reviewed journal articles, articles, and conference papers.	• The articles are authored in a language different from English.
• It should encompass the application of a Machine/Deep learning methods to identify species.	• The papers concentrate on alternative objectives employing machine or deep learning approaches.
• The language of the material must be English	• Explores the identification models for plant and various micro-organism species

The academic papers that did not meet the specified criteria were omitted from the search. The introductory screening phase took place on the entire set of 193 extracted records to filter the search output. These records underwent comparison with pre-selected guidelines, involving narrowing the search parameters to computer science and restricting the results to the last five years. Consequently, the assessed total decreased to 125 papers, which were then evaluated against the mentioned selection standard. Figure 2 illustrates the progression through the pre-selection and selection criteria. Ultimately, this process led to the inclusion of 15 papers in the systematic review focused on species identification and counting using machine learning.

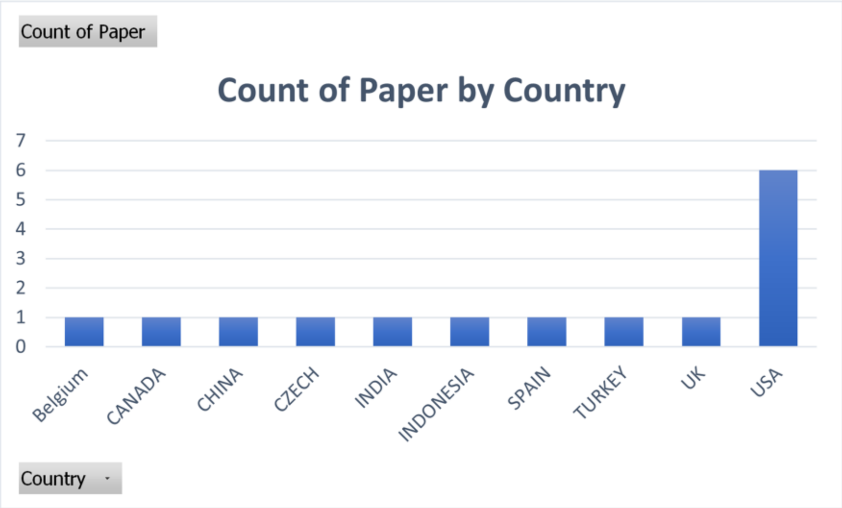

Figure 2. Article distribution by country

3.4. Quality assessment

The guidelines for inclusion and exclusion were carefully selected as the criterion for assessing the formal writing standards within the scope of this paper. The criteria used will determine the quality of the selected papers. The criteria illustrated in Table 4 was used to identify the papers across various journals.

The scoring methodology, adapted from [23], assigns a value of 1 for a 'Yes' response, 0.5 for a 'Moderately' response, and 0 for a 'No' response in the quality assessments questions. Table 5 presents the outcomes, demonstrating that all selected papers have successfully met the quality assessment criteria

Table 4. Quality certainty checklist

Number	Quality Certainty Question
1	Is the articulation of research goals explicit?
2	Are the key points of the investigation presented in a clear and concise manner?
3	Does the study provide in-depth details about its methodology?
4	Does the study provide information about the dataset and methods used?
5	Do the study's results contribute to enhancing our comprehension of deep learning models?
6	Are the limitations of the study clearly delineated?

Table 5. Response to quality assessment questions of selected articles

Study	Q1	Q2	Q3	Q4	Q5	Q6	Total	Percentage
S1	1	1	1	1	1	1	6	100%
S2	1	1	0.5	1	0.5	0.5	4.5	75%
S3	0.5	0.5	0.5	1	0.5	1	4	66.67%
S4	1	0.5	1	1	1	0.5	5	83.33%
S5	1	1	1	1	0.5	1	5.5	91.67%
S6	1	1	0.5	0.5	0.5	1	4.5	75%
S7	0.5	0.5	1	0.5	1	1	4.5	75%
S8	1	1	1	1	0.5	1	5.5	91.67%
S9	1	0.5	1	1	0.5	1	5	83.33%
S10	0.5	0.5	0.5	1	1	0.5	4	66.67%
S11	1	1	0.5	0.5	1	0.5	4.5	75%
S12	0.5	1	1	1	1	0.5	5	83.33%
S13	1	1	0.5	0.5	1	1	5	83.33%
S14	1	1	1	1	0.5	1	5.5	91.67
S15	1	1	1	1	1	1	6	100%

4. RESULTS

Applying the research approach outlined in the preceding section, the identified research question was systematically categorised and assessed across the reviewed papers. Each paper was evaluated based on its specific contributions to the topic, enabling a structured analysis of the research landscape. This process provided a comprehensive understanding of how the research question has been addressed and highlighted key trends and gaps in the existing literature.

4.1. Classification and examination of articles

Examining all 15 articles incorporated in the systematic review involved in the of a classification system according to their respective contributions to addressing the research question. Markings were done to signify whether if the primary objective of each article linked to a particular category. While many other articles concisely discussed various uses of deep learning models, only a few studies concentrated primarily on a specific use or provided comprehensive discussions on several integrations were categorised under ‘Automatic identification using deep learning’. The outcomes of this classification are detailed in Table 6. Furthermore, every paper underwent a thorough assessment, and the outcomes of this precise examination are presented in Table 7. Figure 2 illustrates the count of articles by country. The outcomes indicate a growing activity and improvements done in this subject over the last 5 years. It is evident in the rising number of publications since 2019 that, notably, the majority of this research is centred in the USA.

4.2. Quality assessment results

Applying the criteria listed in Table 4, every article used in this work received a score. The highest possible score for an article is 6. The outcomes for each article are shown in Table 6.

A summary of the results from pertinent systematic review papers concentrating on the use of deep learning methods for species identification is shown in Table 7. Together, these studies advance knowledge of the field's present level of research and shed light on the advantages and disadvantages of applying deep learning to species identification.

A consistent interest in the use of deep learning for species identification has been shown over a variety of publication years, as evidenced by the systematic reviews presented in Table 7. Every paper covers a different area of deep learning for species identification and aims to accomplish a specific goal and with the emphasis more on evaluating various deep learning architectures and techniques. The performance of deep learning models in obtaining high accuracy in species identification tasks is frequently observed among the analyses. Nonetheless, issues like the interpretability of deep learning models, dataset biases, and generalizability to other contexts are common themes that should be considered because of the impact they have when using deep learning methods.

Although the articles included in this paper offer insightful information, it is important to recognize that there are certain limitations. These include differences in research designs and the dynamic nature of the deep learning field, which may have changed after these evaluations were published.

Table 6. Quality assessment outcomes of each paper

Study	Source	Importance of ecology for wildlife conservation	Camera trap images	Machine learning in the field of computer vision	Deep learning	Significance of deep learning methods
S1	[6]	X	X		X	X
S2	[24]	X	X		X	X
S3	[25]	X	X		X	X
S4	[26]		X	X	X	
S5	[27]		X	X	X	X
S6	[4]	X	X		X	
S7	[28]		X		X	X
S8	[29]		X		X	
S9	[10]	X	X		X	X
S10	[30]		X	X		X
S11	[31]				X	
S12	[32]		X		X	
S13	[33]		X		X	
S14	[34]		X	X		X
S15	[35]	X	X		X	X

Table 7. Systematic review articles on the application of deep learning for species identification

Study	Source	Country	Year	Methods	Limitations
S1	[6]	USA	2018	Deep learning models, image analysis	Data availability and bias, model interpretability
S2	[24]	China	2020	Review of convolutional neural networks (CNNs)	Limited focus on specific applications, general overview
S3	[25]	USA	2021	Review of camera trap applications in wildlife management and conservation	Broad scope, less detailed analysis of specific methods
S4	[26]	Indonesia	2022	Review of deep learning for wildlife image recognition	Focus on algorithms and techniques, less on practical implementation
S5	[27]	USA	2018	Review of deep learning for automatic camera-trap image classification	Primarily focuses on existing research, limited discussion of future directions
S6	[4]	USA	2019	Camera trap data analysis, habitat suitability modelling	Limited data on specific species, potential impact of camera placement
S7	[28]	Czech	2021	Remote sensing and habitat modelling	Focus on black-footed ferrets, may not be generalizable to other species
S8	[29]	UK	2022	Deep learning for wild boar identification	Data bias towards specific region and species, potential for overfitting
S9	[10]	Spain	2022	Camera trap configuration comparison	Limited data on effectiveness for all large carnivore species, potential variation in habitat responses
S10	[30]	Canada	2023	Review of deep learning for camera trap-based wildlife monitoring	Broad scope, less in-depth analysis of specific applications and challenges
S11	[31]	USA	2018	Review of deep learning for automatic camera-trap image classification	Similar to article #5, focus on existing research and limitations
S12	[32]	Türkiye	2019	Prototype AI system for camel face identification	Limited data and testing, need for further development and field validation
S13	[33]	USA	2021	Anomaly detection in camera trap images using spatiotemporal features	Primarily focused on methodology, less emphasis on practical applications in wildlife monitoring
S14	[34]	India	2023	Object detector models Classification models	Regarding camels, the lighter ones located in the low-resolution regions of the image (i.e., near the upper stream bar) were often confused with sheep/goats. Furthermore, identification was sometimes incorrect when the animal was positioned to the side
S15	[35]	Belgium	2023	an anchor-based baseline (Faster-RCNN), a density-based baseline (DLA-34), and the proposed architecture (HerdNet).	Limited Dataset Minimal Augmentations

5. DISCUSSION

Research Question 1: What is the importance of ecology for wildlife conservation?

In response to this question, 6 articles explicitly emphasized the importance of ecological monitoring for wildlife conservation. This indicated the growing interest in monitoring wildlife biodiversity or population monitoring for essentially maintaining ecological balance, protecting endangered species, and ensuring long-term sustainability for South Africa's biodiversity and natural resources [4], [6], [10]. Fundamentally, the growing interest in monitoring wildlife biodiversity or population monitoring for essentially maintaining ecological balance, protecting endangered species, and ensuring long-term sustainability for South Africa's biodiversity and natural resources [24], [25]. Moreover, this will minimise the dangers that lie with ecological imbalances, as it will help in avoiding human-wildlife conflict and overpopulation of some species or depletion of food resources.

Research Question 2: What are the camera trap images?

Most of the articles employed in this work mentioned camera traps and their use in conservation management. Camera traps are essential for wildlife conservation in South Africa, as they enable researchers and conservationists to gather important data on the presence, abundance, and behaviour of species in their natural habitats [9], [10]. Although there are many advantages of camera traps [6], managing the amount of human labour needed to process, analyse, and study large volumes of data is difficult. Tabak, *et al.* [4] stated the significance of possessing comprehensive and current knowledge about the location and behaviour of animals in the natural environment could enhance the ability to study and conserve biodiversity.

Research Question 3: What are the uses of machine learning in the field of computer vision?

Kevin, *et al*. [26] and Kutugata, *et al.* [27]. Mentioned about the implementation of machine learning in the domain of computer vision for image processing and performing classification tasks on image data that displays various species. Whereas research performed in [35], [36] comprehensively outlined the advantages of the applications in ecology in terms of counting that will help to monitor the animals.

Research Question 4: What is deep learning?

Based on the titles and available information from the articles used in this paper, it seems that deep learning is used in various ways for camera trap data analysis and wildlife monitoring. Most articles refer to it as a powerful tool for modern-day image analysis [27]. Several articles mention using CNNs, a specific type of deep learning architecture, particularly effective for image recognition and classification tasks [6], [10], [24], [25], [27], [30]

Research Question 5: What is the significance of deep learning methods for wildlife conservation?

Most articles mentioned the significance of deep learning methods for wildlife conservation. According to [27] these methods are revolutionizing wildlife conservation by providing powerful tools for monitoring, protecting, and managing wildlife populations. Norouzzadeh, *et al.* [6] conducted a study on automatic image classification using multitask models and were able to accurately classify images of animals with a classification accuracy of 93.8%. Matin, *et al.* [30] performed transfer learning using VGG16 and RestNet50 on ImageNet dataset to classify animal species. The reason behind employing these model architectures was the extensive image processing capabilities each of them possessed on classifying animals on a larger dataset.

6. CONCLUSION

In summary, this paper sought to conduct a systematic review on the subject of species identification using deep learning models. The primary objective was to gain insights into the role of deep learning models in identifying animal species and explore their applications through the integration of mechanisms such as camera traps, computer vision, and neural networks. The literature review addressed research questions related to the extant ways of identifying animals, the use of camera traps, applications of deep learning models, their role in species identification, and their relevance to wildlife conservation. The systematic literature review involved deriving keywords from the research questions, which were then used to search various databases, peer-reviewed journals, and periodicals, including arXiv, Google Scholar, Science Direct, IEEE Xplore, and Springer Complete journals. Initial searches yielded 218 papers and academic works, and through the application of selection criteria and the PRISMA procedure, the number of papers reviewed was narrowed down to 15. Each of the 15 papers was categorized based on its contribution to the research questions and subjected to analysis. Additionally, a quality assessment was performed on the research papers, resulting in scores ranging from 66.67% to 100%.

FUNDING INFORMATION

Authors state no funding involved.

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability does not apply to this paper as no new data were created or analyzed in this study.

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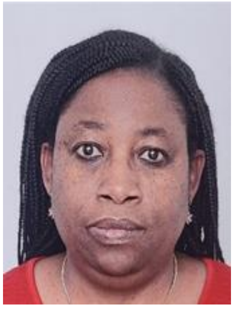

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