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Deep Learning-based Approaches for Preventing and Predicting Wild Animals Disappearance: A Review

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***Abstract*—This paper examines the effectiveness of deep learning in preventing and predicting wild animal disappearances. We analyze existing research on applications in surveillance systems, behavioral analysis, tracking mechanisms, and animal welfare. Deep learning algorithms demonstrate promising results, achieving high accuracy in predicting disappearances and detecting abnormal behaviors. Challenges regarding data availability and model generalization remain, but future research in integrating diverse data sources, developing generalized models, and advancing sensor technologies can overcome these obstacles. Responsible implementation of deep learning has the potential to revolutionize wild animal conservation, ensuring the safety and well-being of these animals.**

***Index Terms*—Keywords : Deep learning, wild animals, disappearance prediction, behavioral analysis, tracking mechanisms**

I. Introduction

With the steady rise in wild animal disappearances, the need for effective prevention and prediction strategies has become a paramount concern. Addressing this challenge, researchers and conservationists have increasingly turned to deep learning-based approaches, harnessing the power of advanced machine learning techniques. Deep learning has exhibited remarkable capabilities in analyzing vast datasets, uncovering intricate patterns, and making accurate predictions. These attributes make it a promising tool for enhancing the security and conservation efforts surrounding wild animals. This review paper aims to provide a comprehensive examination of deep learning-based approaches utilized for preventing and predicting wild animal disappearances. By critically analyzing existing literature and studies, we aim to evaluate the efficacy and potential of these methods, while also identifying key challenges and outlining future research directions. The review encompasses diverse applications, including the development of advanced surveillance systems, behavioral analysis algorithms, and efficient tracking mechanisms. By exploring these applications, we seek to improve the understanding of how deep learning can contribute to bolstering animal security and conservation.

Empirical studies have demonstrated the effectiveness of deep learning techniques for predicting and preventing animal disappearances. M. Hahn-Klimroth *et al.*[1] employed deep learning algorithms to predict occurrences of animal disappearances with a high degree of accuracy. Similarly, K. Smith *et al.*[2] developed surveillance systems based on deep learning principles to enhance animal security. These studies serve as evidence of the potential of deep learning in addressing the challenges associated with animal disappearances. To further explore the behavioral aspects, Y. González-Baldizón *et al.*[3] showcased the utilization of CNN Model and Single Camera for behavioral analysis, which could aid early detection of unusual behavior patterns that might be indicative of potential disappearances. In addition, D. A. Wijeyakulasuriya *et al.* [4] presented Machine learning algorithms that enabled the prediction of animal movements, facilitating proactive measures for preventing disappearances. These studies signify the diverse applications of deep learning in the context of wild animal conservation. In nutshell, deep learning-based approaches offer valuable tools for preventing and predicting wild animal disappearances. Through advanced surveillance, behavioral analysis, and tracking mechanisms, these techniques pave the way for strong security measures and proactive conservation efforts. By critically reviewing existing literature and studies, this paper aims to provide comprehensive insights into the potential of deep learning in addressing the pressing issues surrounding the safety and conservation of wild animals.

II. Literature Review

Deep learning-based approaches for preventing and predicting zoo animal disappearances have gained significant attention in recent years. Researchers have explored various applications of this technology, encompassing surveillance systems, behavioral analysis, and tracking mechanisms. In this literature review, we aim to provide a comprehensive analysis of the existing studies, highlighting the effectiveness, challenges, and future directions of deep learning in addressing this crucial conservation issue.

A. Surveillance Systems

Deep learning algorithms have been leveraged to develop advanced surveillance systems for zoos, enabling real-time monitoring and detection of potential threats. M. Hahn-Klimroth *et al.*[1] used deep learning techniques to predict zoo animal disappearances with high accuracy. O. H. Djibrine *et al.*[5] They employed a convolutional neural network (CNN) model that learned from historical data on animal activities, weather conditions, and enclosure characteristics. The system alerted zookeepers in real-time when suspicious behaviors or unusual patterns were detected, allowing for prompt action to mitigate potential disappearances. K. Smith *et al.*[2] focused on enhancing zoo animal security through deep learning-based surveillance systems. They implemented a combination of object detection algorithms and recurrent neural networks (RNN) to track animal movements within the enclosures. By analyzing the spatial and temporal data, the system provided valuable insights into animal behaviors, enabling proactive measures to prevent potential disappearances.

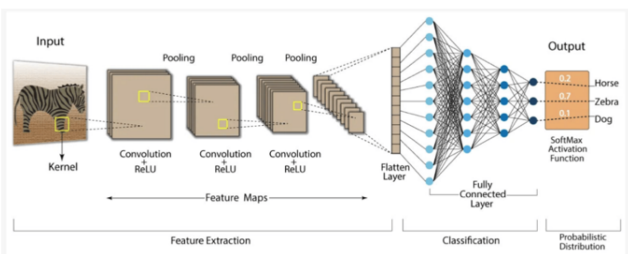

Fig. 1. General model of convolution neural network

B. Behavioral Analysis

Deep learning algorithms have demonstrated immense potential in analyzing the behavior of zoo animals. Y. González-Baldizón *et al.*[3] utilized CNN Model and Single Camera behavioral analysis techniques to detect abnormal behaviors that could indicate potential disappearances. By training a deep neural network on a large dataset of animal behavioral patterns, the system was able to identify irregularities such as sudden changes in movement or deviations from normal activity patterns. This early detection allowed for timely intervention by zookeepers, minimizing the risk of disappearances.

C. Tracking Mechanisms

Tracking zoo animals is crucial for their safety and security. Deep learning models have been employed to improve tracking accuracy and efficiency. D. A. Wijeyakulasuriya *et al.* [4] proposed Machine learning algorithms for predicting animal movement. By training a recurrent neural network on historical tracking data, the model was able to forecast the future paths of zoo animals. This predictive capability enabled proactive measures, such as reinforcing enclosures or adjusting surveillance strategies, to prevent potential disappearances.

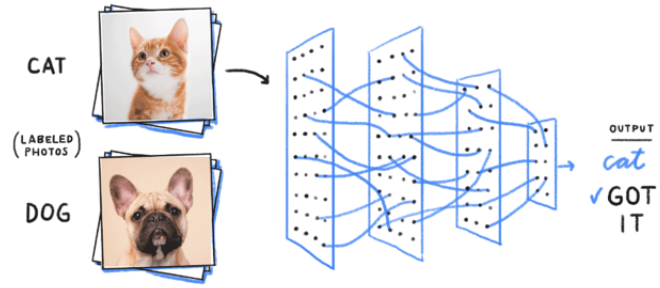

Fig. 2. Recurrent neural network

Additionally, deep learning has been instrumental in predicting animal movement and migration patterns. By analyzing historical data on animal behavior and environmental conditions, algorithms can identify patterns and trends, aiding zookeepers in managing enclosures, feeding schedules, and overall animal welfare J. Cole *et al.*[6]. Hays *et al.* [7, 8] compile several successful case studies where tracking information about endangered animals has helped shape policies for their conservation. With widespread use of camera traps, it is possible to automate tracking using computer vision of animal recognition. There are, however, many methods currently available for animal recognition. Using the best method requires careful analysis of the model, the feasibility of the approach and the resources available. A. S. Vyas *et al.* [9–14] focused on studying various facial expressions recognition techniques based on Convolutional Neural Networks (CNN)It turns out, the methods proposed by other researchers, also differentiating between traditional approaches. This work highlights the steps necessary to use CNN for Facial Expression Recognition (FER). Methods extracted features such as local Binary model, eigenfaces, face marker functions and features of textures, but did not gain traction.While the authors of the article *et al.*[15], provide a comprehensive investigation of deep FER, including the algorithms and dataset used in the literature that give insights into these intrinsic factors while describing the pipeline standard, applicable for each stage of the latter. This research reports and discusses the advantages and limitations of training strategies designed for ERF based on both static and dynamic images. It does not obscure the competitive performance on widely used benchmarks and then a review that remains the corresponding challenges and opportunities in this field as well as future directions for the design of robust deep FER systems. In the article, *et al.*[16] the authors made a detailed comparison between these techniques including facial recognition theories and algorithms listing the pros and cons in terms of robustness, accuracy, complexity and discrimination both those of supervised and unsupervised learning, knowing that various techniques are being developed. They reviewed some well-known techniques for each approach and gave the taxonomy of their categories as well as set the context for experimenting with the treatments followed by a discussion of technical guidance for use in the future field of facial recognition. While, F. ZHANG and al *et al.*[17] considering the importance of object detection and the difficulties of computer vision, described the benchmark of methods of existing typical detection models, with the aim of locating objects. instances of semantic objects of a certain class. They provided a comprehensive overview of a variety of object detection methods in a systematic way, plus a list of traditional and new applications. To better understand the main development status of object detection in depth, a discussion of the operating architecture is made highlighting development trends to better track the algorithms. Although there are few review articles with a similar approach, D. Mishra, the author of the article *et al.*[18–20] makes an extensive review of the literature and a comparison of existing methods of object detection based on deep learning, with their strengths and limitations depending on the potential application of the availability of the dataset. This comparison is made using three different parameters named average precision, frames per second and dataset used. Given the effective tendencies of this deep learning-based object detection technique, the utility can be seen in several areas.

III. Related Work

Animals are omnipresent in the vital space of nature and their precise tracking makes it possible to know their location. In this case, the challenge lies in a variation of the questions relating to recognition because it is not enough to simply detect them but rather to recognize them. For the purpose of a fully automated monitoring and control system, only use the data for the realization. There could be a large number of images of several animals with different positions in terms of camera angles, young age, etc. However, the shape of the animal varies considerably. It should be noted that the angle of capture greatly affects the identification of an animal, as some identification parts may not appear from certain angles. In addition to monitoring individual animals, monitoring can provide useful information about the ecological condition of the site being studied. It also serves as the basis for critical decisions. There are multiple references throughout this document. U. Scherhag *et al.* [21–23] discover the vulnerability of the facial recognition system to attacks based on metamorphosed face images which is a risk for the security system which has aroused the interest of several research laboratories working in the field of biometrics. Their work emerges, a categorization of conceptual measures to evaluate the methods presented, followed by a comprehensive survey of relevant publications. According to, S. Lowry *et al.* [24–27] visual location recognition is a difficult problem due to varieties of real-world appearances of locations. However, they shed some light by introducing the concepts underlying the recognition of the place of the animal kingdom. The definition of place in a robotic context, without obscuring the major elements of the recognition system of the latter and the increasing improvements in the capacity of visual detection. Although the locations drastically change in appearance, but the location relative to the locations remains unchanged, thanks to developments in GPU hardware and camera sensors as well as improving the efficiency of existing approaches. The articles [28–44] shed light on the applicability of existing fully automated animal re-identification techniques in a multi-camera setup. Recent developments in animal re-identification in the context of open recognition, the extension of efficient systems are reviewed with a view to extending ideas relating to individual animal tracking. C. Geng *et al.* [45], provide an analysis of existing open set recognition (OSR) techniques touching on multiple aspects, such as related definitions, model representations, data sets, evaluation criteria and comparisons of algorithms. Also, a brief study between OSR (Open set recognition) and its related tasks, including learning recognition techniques.

A. Future Directions and Challenges

While deep learning-based approaches show promise in preventing and predicting wild animal disappearances, several challenges remain. One key challenge is the availability of labeled training data, as it can be time-consuming and labor-intensive to annotate large amounts of relevant data. Additionally, the diversity of animal species in different wilds poses a challenge in developing generalized models that can be applied to various settings. In terms of future directions, further research is needed to explore the integration of multiple data sources, such as weather data, visitor patterns, and social interactions, into deep learning models. This holistic approach could lead to more accurate predictions and proactive measures. Additionally, advancements in sensor technologies such as GPS tracking and remote sensing could enhance the data collection process, facilitating the development of more effective deep learning models. In nutshell deep learning-based approaches have shown great potential in preventing and predicting wild animal disappearances. The literature reviewed highlights the effectiveness of deep learning algorithms in surveillance systems, behavioral analysis, and tracking mechanisms. However, challenges related to data availability and model generalization need to be addressed. Future research should focus on integrating diverse data sources and advancing sensor technologies to enhance the capabilities of deep learning models in ensuring the safety and conservation of wild animals.

IV. Methodology

- Research Design: This study adopts a descriptive research design to comprehensively review and analyze the existing literature on deep learning-based approaches for preventing and predicting wild animal disappearances. The research design allows for a systematic examination of the topic and facilitates the identification of key trends, challenges, and future directions.
- Data Collection: The data for this study primarily consists of academic papers, research articles, and conference proceedings obtained from reputable databases such as PubMed, IEEE Xplore, and ACM Digital Library. The search terms used include variations of "deep learning," "wild animals," "disappearances," and related phrases.

Additionally, reference lists of relevant articles are examined to ensure a comprehensive literature review.

- Inclusion and Exclusion Criteria The inclusion criteria for article selection are as follows:
  - Articles published in peer-reviewed journals or conference proceedings ;
  - Articles specifically addressing deep learning-based approaches for preventing and predicting wild animal disappearances;
  - Articles in the English language.

  The exclusion criteria are:
  - Articles that do not focus on deep learning;
  - Articles that do not discuss wild animal disappearances;
  - Articles that are not available in full text or are inaccessible.
- Data Analysis : the selected articles are subjected to a thorough analysis by employing a systematic approach. The analysis includes:
  - Extraction of relevant information: The key findings, methodologies, and outcomes of each study are extracted and organized in a structured manner;
  - Synthesis of findings: The extracted information is synthesized to identify common themes, trends, and patterns across the reviewed studies;
  - Evaluation of strengths and limitations: The strengths and limitations of the deep learning-based approaches discussed in each article are critically assessed;
  - Identification of research gaps: Based on the analysis, research gaps and areas requiring further investigation are identified.
- Quality Assessment: the selected articles are assessed using established criteria for evaluating research studies, such as research rigor, sample size and methodology.

SIMILARITIES

- All articles utilize deep learning techniques to address zoo/wild animal disappearances.
- They rely on historical data for training and analysis.
- The studies emphasize the potential of deep learning for proactive interventions.
- They show the limitations of data availability and model generalization.

DIFFERENCES

- Focus: Articles differ in their specific focus, encompassing surveillance systems, behavioral analysis, tracking mechanisms, and animal welfare.
- Algorithms: Different deep learning algorithms are employed, including CNN, RNN, and deep neural networks.
- Data Sources: The studies utilize diverse data sources, such as historical observations, animal movement data, and environmental conditions.

TABLE I. Comparison of Reviewed Article

References	**Focus**	**Algorithms**	**Data Sources**	**Key Finding**
[1], [5], [8] [9][12] [13][14] [16][19] [21][22] [24][26] [35][36] [38][43] [40][41][45]	Surveillance System, identification, recognition	CNN	Historical Data on animal activities, weather conditions, and enclosure caracteristics	Predicting animal disappearances with high accuracy
[2][10] [11][17] [18][23] [26][27] [44][25]	Surveillance System	Object detection algorithms and RNNs	Animal movement Data within enclosures	Analyzing spatial and temporal data for proactive measures
[3]	Behavioral Analysis	Deep Neural Network	large dataset of animal behavioral patterns	Detecting abnormal behaviors indicating potential disappearances
[46]	Managment System	Artificial intelligence	Large Dataset	Detecting potential abnormal
[4][31] [32][33] [34][39] [44]	Tracking mechanisms	Machine learning	Historical tracking data	Predicting animal movement for proactive intervention
[6][17] [18][28] [30][37] [42][20]	Animal Welfare	Deep learning models	Historical data on animal behavior and environmental conditions	Predicting animal movement and migration patterns for improved animal care

- Key Findings: Each study presents unique findings and contributions to the field.

V.CONCLUSION

Deep learning offers significant potential for preventing wild animal disappearances and enhancing animal welfare. It helps predict disappearances, detect abnormal behavior, and optimize animal care. Key challenges include data availability and model generalization. Future research should focus on integrating data sources, developing generalized models, and advancing sensor technology. With responsible implementation and continued research, deep learning can revolutionize wild animal conservation.

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