International Journal of Informatics, Information System and Computer Engineering

INJIISCOM

Deep Learning for Sea Turtle Classification: A Bibliometric Analysis Using VOSviewer

Siti NurFarahim, Azran Shabil, Nur Sabrina Balqis*

Faculty of Ocean Engineering Technology and Informatics, Universiti Malaysia Terengganu, Terengganu, Malaysia
*Corresponding Email: farahfarahim@gmail.com

ABSTRACTS

Deep learning in the context of sea turtles constitutes a significant area of exploration within marine science. Consequently, the aim of this study is to perform a bibliometric analysis focusing on the subject of sea turtle deep learning, leveraging mapping analysis through the utilization of VOSviewer software. For this research, we employed a bibliometric and descriptive quantitative approach. The data was acquired by conducting a search on Google Scholar using the keyword "Sea Turtle Deep Learning," which yielded a total of 880 articles published between 2018 and 2023. Notably, only 19 of these articles were directly relevant to the research topic. The findings underscore the diversity of research outcomes in the realm of sea turtle deep learning over this time span. In conclusion, this investigation underscores the significance of conducting bibliometric analyses, particularly within the domain of sea turtle deep learning, and serves as a valuable reference for future research endeavours in defining research themes.

ARTICLE INFO

Article History:
Received 10 Jan 2024
Revised 21 Jan 2024
Accepted 18 Feb 2024
Available online 11 Mar 2024
Publication Date 01 Jun 2024

Keywords:
Technology,
Information System,
Computer Science

1. INTRODUCTION

Sea turtle research, based on deep learning, has gained significant traction among marine scientists due to the current vulnerable and endangered status of sea turtles, as noted in (Kittinger et al., 2013). Identifying individual sea turtles holds crucial importance for comprehending their behavior, life history, evaluating threats, assessing anthropogenic impacts, and understanding population dynamics (Blumenthal et al., 2009; Wallace et al., 2010; Casale et al., 2013). Deep learning serves as a technique for classifying and identifying sea turtles by employing image recognition methods in computer vision. Previous studies have indicated the widespread use of deep learning in the classification and recognition of sea turtles. Although a limited number of papers have been published on sea turtle identification, focusing primarily on species recognition (Attal & Direkoglu, 2020; Liu et al., 2020; Fauria et al., 2023), one particular study (Papafitsoros et al., 2022) emphasized the detrimental effects of tagging on sea turtles. This study remains the only literature found via manual internet searches to date. However, there are immense opportunities to explore specific themes and conduct extensive research in this field. Given the importance of the topic, it is crucial to conduct a bibliometric study to examine this subject. Bibliometric studies can track trends, identify influential authors or publications, measure the impact of research, and understand the interconnections between different areas of study (Butticè, & Ughetto, 2023). VOSviewer (Arruda et al., 2022), a widely-used software tool for constructing and visualizing bibliometric networks, has been utilized in this research. This tool is commonly employed in bibliometrics to analyze and illustrate relationships between different scholarly publications, authors, or keywords. In the realm of deep learning, various researchers have implemented analytical tasks. For example, Bidwe et al. conducted a bibliometric study on Deep Learning Approaches for Video Compression (Bidwe et al., 2022), where they discussed the bibliometric analysis and literature survey of all Deep Learning (DL) methods used in video compression based on Scopus and Web of Science database journal library. Similarly, Coulibaly et al. performed a bibliometric analysis based on deep learning for precision agriculture, revealing the extensive involvement of deep learning in digitizing agricultural areas with higher accuracy compared to standard image processing techniques (Coulibaly et al., 2022). In the healthcare field, Khairi et al. proposed Deep Learning on Histopathology Images for Breast Cancer Classification (Khairi et al., 2021), where they focused on annual publication trends, co-authorship networks among countries, authors, and scientific journals. They analyzed the co-occurrence network of authors' keywords for potential future directions in the field. Nevertheless, research on bibliometric analysis concerning sea turtle classification remains scarce, especially regarding the utilization of VOSviewer software as a tool for conducting mapping analysis. Therefore, this research aims to conduct a bibliometric analysis in the field of sea turtle classification, integrating mapping with VOSviewer software. This analysis is crucial to ascertain the quantity and novelty of data and is expected to serve as a valuable resource for academics in determining and selecting research subjects, particularly those related to sea turtle classification.

2. MATERIALS AND METHOD

The research employed bibliometric and descriptive quantitative approaches. Data were collected from published journals indexed by Google Scholar due to its convenient accessibility. VOSviewer 1.6.17 was utilized to gather the data, filter relevant materials, and extract information specifically related to deep learning sea turtle classification. By inputting the keyword "deep learning sea turtle" in VOSviewer, we retrieved 880 data entries, which were subsequently refined to 19 related journals. The study encompassed publications from 2018 to 2023, with the collected articles stored in *.ris format. Subsequently, we employed VOSviewer software to visualize and analyze bibliometric trends through the generated bibliometric maps. The article data from the compiled database sources were mapped using the VOSviewer software, which facilitated the categorization of data visualization into network, overlay, and density formats. Furthermore, the terms included in the VOSviewer mapping visualization were filtered to ensure relevance and accuracy.

3. RESULTS AND DISCUSSION

3.1. Research developments in the field of deep learning sea turtle

Figure 1 illustrates the progression of deep learning sea turtle research from 2018 to 2023. As indicated in the figure, the development of deep learning sea turtle research over the past five years experienced growth from 2018 to 2021, followed by a subsequent decline in 2022. Notably, in 2023, there was a significant decrease in the number of publications.

Specifically, the number of articles in 2018 was 112, which then increased to 160 in 2019. The upward trend continued with a further increase to 236 articles in 2020. Subsequently, in 2021, the number of articles continued to rise to 241. However, there was a decrease in 2022, with the number of articles dropping to 158. The trend continued in 2023, with the number of articles plummeting to 52.

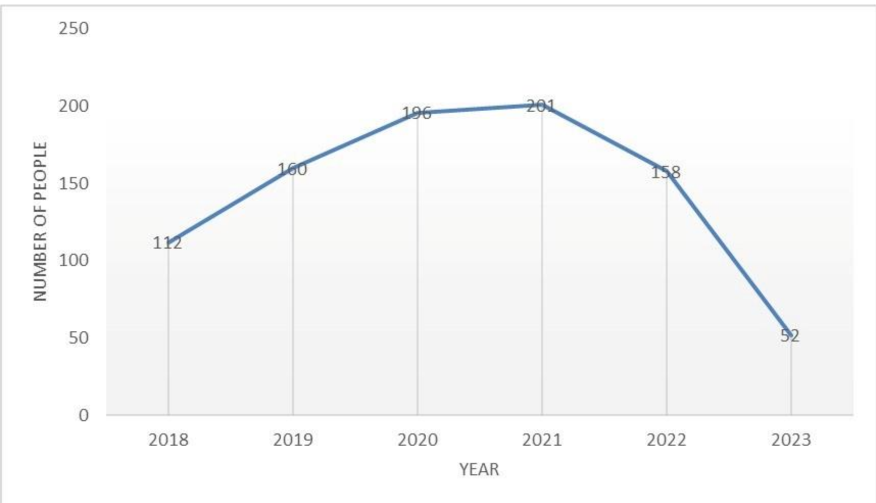

Fig. 1. Levels of development of research on deep learning sea turtle

Figure 1 indicates an upward trajectory in deep learning sea turtle research from 2018 until a decline in 2022, with a further reduction to 92 publications in 2023, down from 201 in 2022. Furthermore, a total of 880 articles relevant to the research topic were initially identified, and following rigorous filtration, 19 articles with the highest citations were selected from distinct journals, as shown in Table 1. The table displays data pertaining to the selected 19 articles, revealing that the maximum citations for a single article in the realm of deep learning sea turtles reached 1974 in 2018, while the lowest was recorded at 168 in 2020. Table 1 shows summarized of all the 19 articles.

Table 1. Article Data in the Field of Deep Learning Sea Turtle

No	Authors	Title	Year	Cites	Refs
1.	N Akhtar et al.	Threat of adversarial attacks on deep learning in computer vision: A survey	2018	1974	(Akhtar et al., 2018)
2.	A Athalye et al.	Synthesizing robust adversarial examples	2018	1594	(Athalye et al., 2018)
3.	A Carr	Handbook of turtles: the turtles of the United States, Canada, and Baja California	2018	1389	(Lorus et al., 2018)
4.	G Marcus	Deep learning: A critical appraisal	2018	1389	(Marcus et al., 2018)
5.	T Solomon et al.	… of patients admitted to hospital with covid-19 using the ISARIC WHO Clinical Characterisation Protocol: development and validation of the 4C Mortality Score	2020	1366	(Solomon et al., 2020)
6.	O Stephen et al.	An efficient deep learning approach to pneumonia classification in healthcare	2019	496	(Stephen et al., 2019)
7.	H Wang et al.	Learning robust global representations by penalizing local predictive power	2019	449	(Wang et al., 2019)
8.	Y Wang et al.	A comparison of word embeddings for the biomedical natural language processing	2018	374	(Wang et al., 2018)
9.	B Mitra et al.	An introduction to neural information retrieval	2018	342	(Craswell et al., 2018)
10.	BG Weinstein	A computer vision for animal ecology	2018	312	(Weinstein, 2018)
11.	K Min et al.	Ranking environmental degradation trends of plastic marine debris based on physical properties and molecular structure	2020	301	(Min et al., 2020)
12.	MP Jensen et al.	Environmental warming and feminization of one of the largest sea turtle populations in the world	2018	291	(Jensen et al., 2018)
13.	V	Analysis of explainers of black box	2021	273	(Buhrmester

No	Authors	Title	Year	Cites	Refs
	Buhrmester et al.	deep neural networks for computer vision: A survey			et al., 2021)
14.	A Chatterjee et al.	SemEval-2019 task 3: EmoContext contextual emotion detection in text	2019	249	(Chatterjee et al., 2019)
15.	F Fang et al.	Cryptocurrency trading: a comprehensive survey	2022	230	(Fang et al., 2022)
16.	J Degrave et al.	A differentiable physics engine for deep learning in robotics	2019	204	(Degrave et al., 2019)
17.	M Zhao et al.	Applications of satellite remote sensing of nighttime light observations: Advances, challenges, and perspectives	2019	184	(Zhao et al., 2019)
18.	S Kong et al.	Evaluation of individual and ensemble probabilistic forecasts of COVID-19 mortality in the United States	2022	182	(Cramer et al., 2022)
19.	N Alswaidan et al.	A survey of state-of-the-art approaches for emotion recognition in text	2020	168	(Alswaidan et al., 2020)

3.2. Visualization of deep learning sea turtle topic area using VOSviewer

According to Al Husaeni and Nandiyanto (Husaeni & Nandiyanto, 2023), in the VOSviewer application, the minimum number of relationships is set by 2 terms. However, in this study, the minimum number of relationships in the VOSviewer between terms is 3. Therefore, the results obtained are 19 items with a total of 5 clusters. Research related to deep learning sea turtle based on visualization mapping analysis is divided into 5 clusters, namely:

- **i.** Cluster 1 has 13 items, the 13 items are recognition, detection, classification algorithm, performance, classification accuracy, deep neutral network, neutral network, convolutional neutral network, cnn, image classification, deep convolutional neural network, artificial intelligence, and computer vision (See Figure 2).
- **ii.** Cluster 2 has 10 items, the 10 items are deep neural network, neural network, computer vision, network, artificial intelligence, classification task, image classification, cnn, convolutional neural network, and object detection (See Figure 3).
- **iii.** Cluster 3 has 8 items, the 8 items are deep convolutional neural network, object detection, cnn, image classification, classification task, deep neural network, recognition, and neural network (See Figure 4).
- **iv.** Cluster 4 has 7 items, the 7 items are network, artificial intelligence, classification algorithm, neural network, detection, deep neural network, performance (See Figure 5).
- **v.** Cluster 5 has 6 items, the 6 items are cnn, sea turtle species, convolutional neural network, deep learning algorithm, object detection, image classification, and deep

convolutional neural network (See Figure 6).

Cluster 1 is displayed in red, Cluster 2 is displayed in green, Cluster 3 is displayed in blue, Cluster 4 is displayed in yellow, and Cluster 5 is displayed in purple.

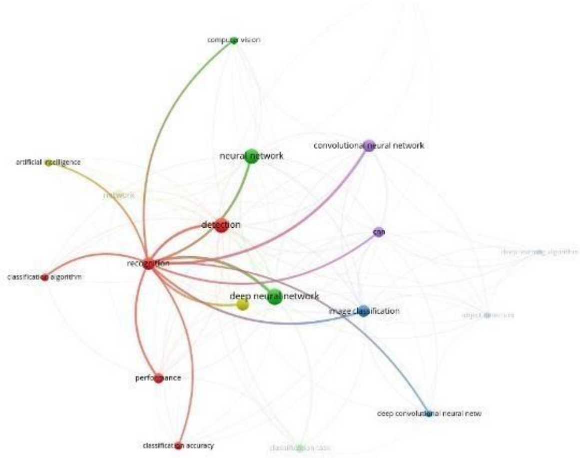

Fig. 2. Cluster 1 Network visualization of deep learning sea turtle.

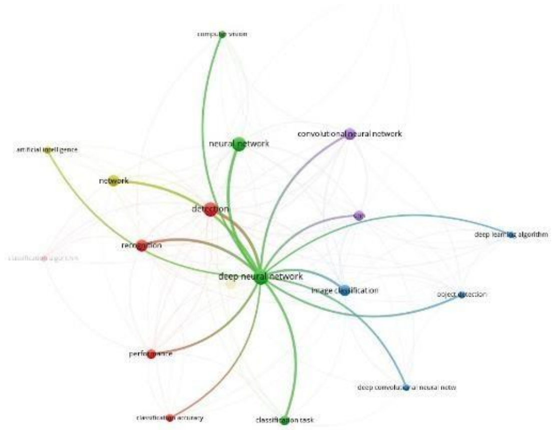

Fig. 3. Cluster 2 Network visualization of deep learning sea turtle.

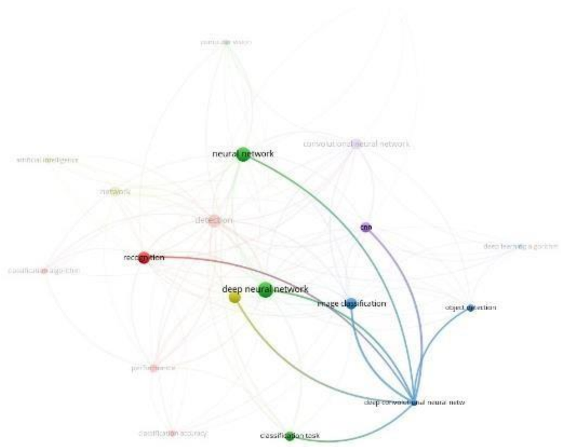

Fig. 4. Cluster 3 Network visualization of deep learning sea turtle.

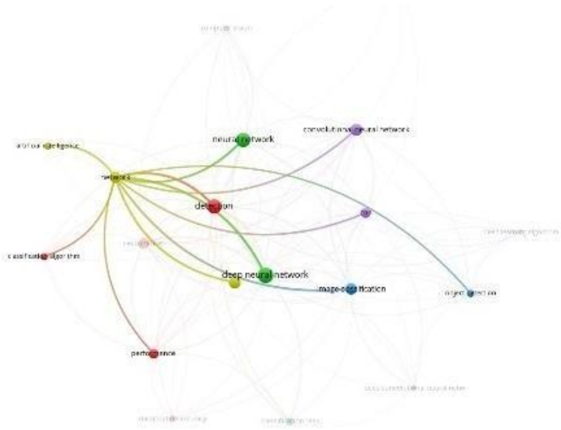

Fig. 5. Cluster 4 Network visualization of deep learning sea turtle.

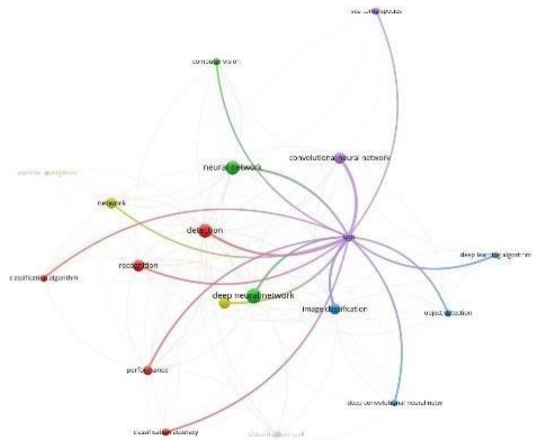

Fig. 6. Cluster 5 Network visualization of deep learning sea turtle.

3.3. Network visualization deep learning sea turtle topic area using VOSviewer

Within the VOSviewer application, term mapping is categorized into three types, one of which is Network Visualization. This form of visualization illustrates the interrelationships among terms on a map. Connections between terms are represented by lines or networks extending from one term to another. Figure 8 presents the Network Visualization of the term 'Deep Learning Sea Turtle' derived from the VOSviewer application. Additionally, Figure 7 depicts the visualization of each cluster within the researched topic areas. Notably, as observed in Figure 7, the term 'deep neural network' exhibits the highest connectivity, being prevalent across all clusters.

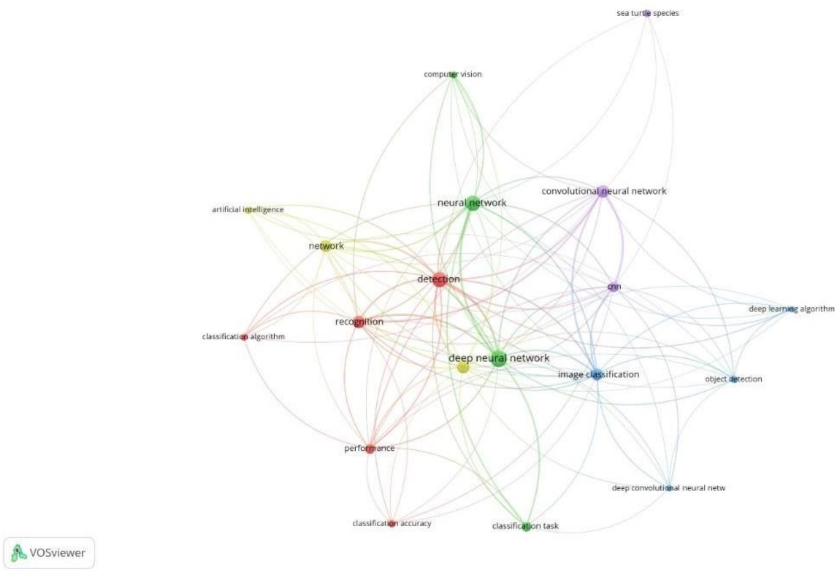

Fig. 7. Network visualization of deep learning sea turtle.

3.4. Overlay visualization deep learning sea turtle topic area using VOSviewer

Apart from Network Visualization, the VOSviewer application also offers an overlay depiction as a form of mapping. Overlay Visualization focuses on assessing the novelty of a term within the research context. Figure 8 demonstrates the representation of term novelty in research related to 'Deep Learning Sea Turtle'. In this type of term mapping, the popularity of a term over the years is illustrated. The colors in the Overlay Visualization represent the recency of a term within a specific timeframe. Within the scope of this study, the period from 2018 to 2023 was considered. A darker color tending towards purple signifies that research on a term was more prevalent closer to 2018. On the other hand, a lighter color leaning towards yellow indicates that the term appeared more frequently in recent research.

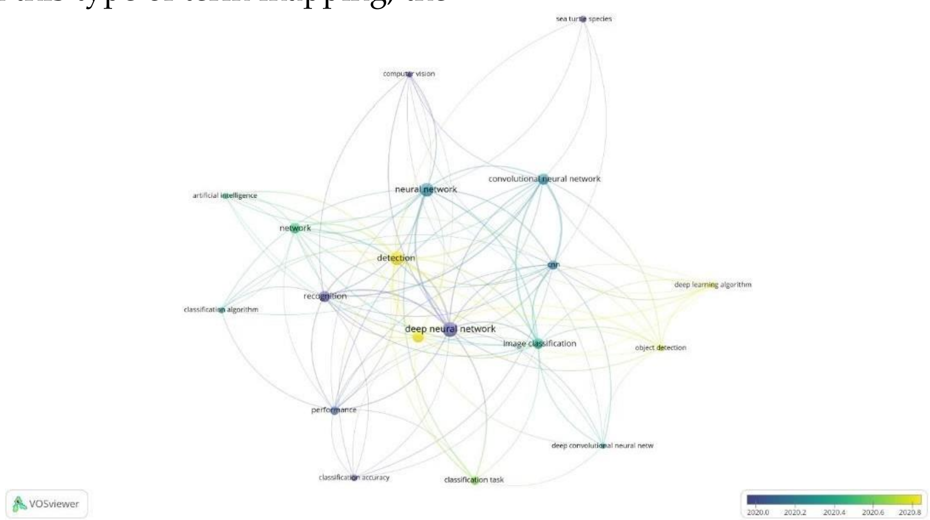

Fig. 8. Overlay visualization of deep learning sea turtle

Figure 8 exhibits an overlay visualization, where 'deep learning sea turtle' emerges as a highly sought-after research keyword, trailing behind 'emissions' and 'food'. As depicted in Figure 8, 'deep learning sea turtle' is interconnected with 18 other terms. Terms associated with 'deep learning sea turtle' encompass 'deep neural network', 'artificial intelligence', 'classification algorithm', 'network', 'recognition', 'performance', 'computer vision', 'neural network', 'detection', 'classification accuracy', 'convolutional neural network', 'CNN', 'image classification', 'deep convolutional neural network', 'object detection', 'deep learning algorithm', 'sea turtle species', and 'classification task'. The overlay visualization effectively demonstrates the evolution of studies over time and the interrelationships among these terms.

3.5. Desity visualization of Deep Learning Sea Turtle

The VOSviewer application encompasses the last type of mapping depiction known as Density Visualization. This representation categorizes each term based on its prominence within research. Figure 9 illustrates the Density Visualization of 'Deep Learning Sea Turtle'. This form of mapping is discernible through the color gradations of each term. A lighter color signifies that research on a particular term is gaining prominence or increasing. Conversely, a darker or more faded color indicates a decline or reduced frequency in research related to that term. In Figure 9, several terms, including 'deep neural network', 'detection', and 'neural network', appear as yellow with significant diameters. This suggests that these terms are frequently employed within existing studies. The density map, derived from the analysis of all articles on deep learning sea turtles from 2018 to 2023, reveals a pattern of yellow shades. The intensity of the yellow color and the size of the circle correlate with the frequency of these keywords. Conversely, fading or blending colors against the green background indicate that these keywords appear less frequently. This outcome underscores the efficacy of bibliometric analysis in exploring and visualizing the current literature, thereby providing a foundation for deciding the need for further research.

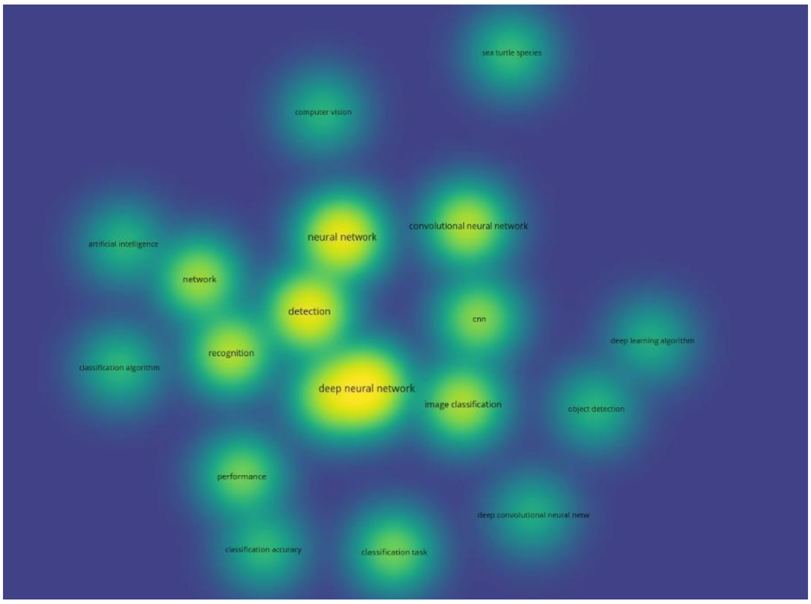

Fig. 9. Density visualization of deep learning sea turtle.

4. CONCLUSION

This study aims to conduct a bibliometric analysis of the literature concerning deep learning sea turtles. The keyword "deep learning sea turtle" was employed to retrieve data, encompassing relevant topic areas within abstracts, titles, and keywords. After data filtration, a selection of 19 pertinent articles was obtained. The mapping data was processed using the VOSviewer software, generating network, overlay, and density visualizations. Analysis of the mapping findings through VOSviewer indicated a declining trend in sea turtle research involving deep learning from 2018 to 2023. This study employed bibliometric methods to identify key themes within previous research, offering valuable insights for evaluating the potential areas of novelty in future research.

ACKNOWLEDGMENTS

We extend our heartfelt thanks to Dr. Senny Luckyardi for providing guidance and showing unwavering commitment in reviewing this research.

REFERENCES

Akhtar, N., & Mian, A. (2018). Threat of adversarial attacks on deep learning in Computer Vision: A survey. In arXiv [cs.CV]. http://arxiv.org/abs/1801.00553

Alswaidan, N., & Menai, M. E. B. (2020). A survey of state-of-the-art approaches for emotion recognition in text. Knowledge and Information Systems, 62(8), 2937–2987.

Arruda, H., Silva, E. R., Lessa, M., Proença Jr, D., & Bartholo, R. (2022). VOSviewer and bibliometrix. Journal of the Medical Library Association: JMLA, 110(3), 392.

Athalye, A., Engstrom, L., Ilyas, A., & Kwok, K. (2017). Synthesizing robust adversarial examples. In arXiv [cs.CV]. http://arxiv.org/abs/1707.07397

Attal, Z., & Direkoglu, C. (2020). Sea turtle species classification for environmental research and conservation. In Advances in Intelligent Systems and Computing (pp. 580– 587). Springer International Publishing.

Balakrishnan, G., Velavan, R., Batoo, K. M., & Raslan, E. H. (2020). Microstructure, optical and photocatalytic properties of MgO nanoparticles. *Results in Physics*, *16*, pp. 103013.

Bidwe, R. V., Mishra, S., Patil, S., Shaw, K., Vora, D. R., Kotecha, K., & Zope, B. (2022). Deep Learning approaches for video compression: A bibliometric analysis. Big Data and Cognitive Computing, 6(2), 44.

Blumenthal, J. M., Austin, T. J., Bothwell, J. B., Broderick, A. C., Ebanks-Petrie, G., Olynik, J. R., Orr, M. F., Solomon, J. L., & Witt, M. J. (2009). Effects of local ecological knowledge and training on the accuracy of sea turtle nesting surveys. Conservation Biology, 23(5), 1130–1141.

Buhrmester, V., Münch, D., & Arens, M. (2021). Analysis of explainers of black box Deep Neural Networks for Computer Vision: A survey. Machine Learning and Knowledge Extraction, 3(4), 966–989.

Butticè, V., & Ughetto, E. (2023). What, where, who, and how? A bibliometric study of crowdfunding research. IEEE Transactions on Engineering Management, 70(9), 3078– 3099.

Casale, P., Margaritoulis, D., Broderick, A. C., Freggi, D., Giovannotti, M., Godley, B. J., Hochscheid, S., Luschi, P., Mazaris, A. D., & Panagopoulou, A. (2013). Sea turtle conservation in italy: Assessing the needs of the loggerhead turtle (Caretta caretta) in the mediterranean sea. Aquatic Conservation: Marine and Freshwater Ecosystems, 23(5), 675–684.

Chatterjee, A., Narahari, K. N., Joshi, M., & Agrawal, P. (2019). SemEval-2019 Task 3: EmoContext Contextual Emotion Detection in Text. Proceedings of the 13th International Workshop on Semantic Evaluation.

Coulibaly, S., Kamsu-Foguem, B., Kamissoko, D., & Traore, D. (2022). Deep learning for precision agriculture: A bibliometric analysis. Intelligent Systems with Applications, 16(200102), 200102.

Cramer, E. Y., Ray, E. L., Lopez, V. K., Bracher, J., Brennen, A., Castro Rivadeneira, A. J., Gerding, A., Gneiting, T., House, K. H., Huang, Y., Jayawardena, D., Kanji, A. H., Khandelwal, A., Le, K., Mühlemann, A., Niemi, J., Shah, A., Stark, A., Wang, Y., … Reich, N. G. (2022). Evaluation of individual and ensemble probabilistic forecasts of COVID-19 mortality in the United States. Proceedings of the National Academy of Sciences of the United States of America, 119(15), e2113561119.

Craswell, N., Croft, W. B., de Rijke, M., Guo, J., & Mitra, B. (2018). Neural information retrieval: introduction to the special issue. Information Retrieval, 21(2–3), 107–110.

Degrave, J., Hermans, M., Dambre, J., & Wyffels, F. (2019). A differentiable physics engine for deep learning in robotics. Frontiers in Neurorobotics, 13, 6.

Dobrucka, R. (2018). Synthesis of MgO nanoparticles using Artemisia abrotanum herba extract and their antioxidant and photocatalytic properties. *Iranian Journal of Science and Technology, Transactions A: Science*, *42*(2), pp. 547-555.

Essien, E. R., Atasie, V. N., Okeafor, A. O., & Nwude, D. O. (2020). Biogenic synthesis of magnesium oxide nanoparticles using Manihot esculenta (Crantz) leaf extract. *International Nano Letters*, *10*(1), pp. 43-48.

Fang, F., Ventre, C., Basios, M., Kanthan, L., Martinez-Rego, D., Wu, F., & Li, L. (2022). Cryptocurrency trading: a comprehensive survey. Financial Innovation, 8(1).

Faurina, R., Wijanarko, A., Heryuanti, A. F., Ishak, S. I., & Agustian, I. (2023). Comparative study of ensemble deep learning models to determine the classification of turtle species. Computer Science and Information Technologies, 4(1), 24–32.

Garrett, D. E. (2012). *Potash: deposits, processing, properties and uses*. Springer Science & Business Media.

Husaeni, D. F., & Nandiyanto, A. B. D. (2023). Mapping visualization analysis of computer science research data in 2017-2021 on the google scholar database with vosviewer”. International Journal of Informatics, Information System and Computer Engineering (INJIISCOM), 3(1), 1–18.

Jensen, M. P., Allen, C. D., Eguchi, T., Bell, I. P., LaCasella, E. L., Hilton, W. A., Hof, C. A. M., & Dutton, P. H. (2018). Environmental warming and feminization of one of the largest sea turtle populations in the world. Current Biology: CB, 28(1), 154-159.e4.

Khairi, S., Bakar, M., Alias, M., Bakar, S., Liong, C.-Y., Rosli, N., & Farid, M. (2021). Deep learning on histopathology images for breast cancer classification: A bibliometric analysis. Healthcare (Basel,Switzerland),10(1), 10.

Kittinger, J. N., Houtan, K. S. V., McClenachan, L. E., & Lawrence, A. L. (2013). Using historical data to assess the biogeography of population recovery. Ecography, 36(8), 868- 872.

Liu, J., Wang, M., Bao, L., Li, X., Sun, J., & Ming, Y. (2020). Classification and recognition of turtle images based on convolutional neural network. IOP Conference Series. Materials Science and Engineering, 782(5), 052044.

Lorus, J., & Milne, M. J. (2018). Handbook of turtles: The turtles of the United States, Canada, and Baja California. Archie Carr. Ithaca, N. y.: Comstock pub., Cornell univ. Press, 1952. 542 pp. $7.50. Science (New York, N.Y.), 116(3007), 181–181.

Marcus, G. (2018). Deep learning: A critical appraisal. In arXiv [cs.AI]. http://arxiv.org/abs/1801.00631

Mguni, L. L., Mukenga, M., Jalama, K., & Meijboom, R. (2013). Effect of calcination temperature and MgO crystallite size on MgO/TiO2 catalyst system for soybean oil transesterification. *Catalysis Communications*, *34*, pp. 52-57.

Min, K., Cuiffi, J. D., & Mathers, R. T. (2020). Ranking environmental degradation trends of plastic marine debris based on physical properties and molecular structure. Nature Communications, 11(1), 727.

Nandatamadini, F., Karina, S., Nandiyanto, A. B. D., & Ragadhita, R. (2019). Feasibility study based on economic perspective of cobalt nanoparticle synthesis with chemical reduction method. *Cakra Kimia (Indonesian E-Journal of Applied Chemistry)*, *7*(1), pp. 61-68.

Nandiyanto, A. B. D. (2018). Cost analysis and economic evaluation for the fabrication of activated carbon and silica particles from rice straw waste. *Journal of Engineering Science and Technology*, *13*(6), pp. 1523-1539.

Nassar, M. Y., Mohamed, T. Y., Ahmed, I. S., & Samir, I. (2017). MgO nanostructure via a sol-gel combustion synthesis method using different fuels: an efficient nano-adsorbent for the removal of some anionic textile dyes. *Journal of Molecular Liquids*, *225*, pp. 730-740.

Papafitsoros, K., Adam, L., Čermák, V., & Picek, L. (2022). SeaTurtleID: A novel long-span dataset highlighting the importance of timestamps in wildlife re-identification.

Prasanth, R., Kumar, S. D., Jayalakshmi, A., Singaravelu, G., Govindaraju, K., & Kumar, V. G. (2019). Green synthesis of magnesium oxide nanoparticles and their antibacterial activity. *Indian Journal of Geo Marine Sciences*, 48(08), pp. 1210-1215.

Solomon, T. (2020). … of patients admitted to hospital with covid-19 using the ISARIC WHO Clinical Characterisation Protocol: development and validation of the 4C Mortality Score.

Stephen, O., Sain, M., Maduh, U. J., & Jeong, D.-U. (2019). An efficient deep learning approach to pneumonia classification in healthcare. Journal of Healthcare Engineering, 2019, 4180949.

Wallace, B. P., DiMatteo, A. D., Hurley, B. J., Finkbeiner, E. M., Bolten, A. B., Chaloupka, M. Y., Hutchinson, B. J., Abreu-Grobois, F. A., Amorocho, D., Bjorndal, K. A., Bourjea, J., Bowen, B. W., Dueñas, R. B., Casale, P., Choudhury, B. C., Costa, A., Dutton, P. H., Fallabrino, A., Girard, A., … Mast, R. B. (2010). Regional management units for marine turtles: A novel framework for prioritizing conservation and research across multiple scales. PloS One, 5(12), e15465.

Wang, H., Ge, S., Xing, E. P., & Lipton, Z. C. (2019). Learning robust global representations by penalizing local predictive power. In arXiv [cs.CV]. http://arxiv.org/abs/1905.13549

Wang, Y., Liu, S., Afzal, N., Rastegar-Mojarad, M., Wang, L., Shen, F., Kingsbury, P., & Liu, H. (2018). A comparison of word embeddings for the biomedical natural language processing. Journal of Biomedical Informatics, 87, 12–20.

Weinstein, B. G. (2018). A computer vision for animal ecology. The Journal of Animal Ecology, 87(3), 533–545.

Zhang, H., Hu, J., Xie, J., Wang, S., & Cao, Y. (2019). A solid-state chemical method for synthesizing MgO nanoparticles with superior adsorption properties. *RSC advances*, *9*(4), pp. 2011-2017.

Zhao, Zhou, Li, Cao, He, Yu, Li, Elvidge, Cheng, & Zhou. (2019). Applications of satellite remote sensing of nighttime light observations: Advances, challenges, and perspectives. *Remote Sensing*, 11(17), 1971.