Deep Learning Formal Models: A Bibliometric Exploration

Angham Boukhari[1,*], Aïcha Choutri[2], Faiza Belala[2], Ahmed Hadj Kacem[1] and Riad Helal[2]

[1]*University of Sfax, ReDCAD Laboratory, BP 1088, 3018 Sfax, Tunisia*
[2]*University of Constantine 2-Abdelhamid Mehri, LIRE Laboratory, BP: 67A, Constantine, Algeria*

Abstract

The growing field of Deep Learning (DL) and Deep Neural Networks (DNN) has seen significant advancements in recent years, particularly in the application of Formal Models to improve system performance and reliability. This study conducts a bibliometric analysis using data from Scopus to explore trends in formal analysis and formal verification of DNN, which are essential for safety-critical applications such as healthcare and autonomous systems. Python and R were employed for data extraction, processing, and visualization. The results emphasize increasing interest in the field, highlight prominent authors, significant author collaborations, key publications, and trends in keywords and research topics. These findings, visualized through tables and graphs, provide insights into the current research landscape and offer guidance for future studies on integrating formal models with DL.

Keywords

Bibliometric Analysis, Deep Learning, Deep Neural Networks, Formal Models, Performance, Formal Analysis, Formal Verification, Scopus

1. Introduction

The origins of Deep Learning (DL) trace back to the 1940s [1], but its growth surged in the 2000s due to advances in computational power, large datasets, and optimization algorithms. As a subset of Machine Learning (ML) [2], DL has driven progress in image and video recognition, audio processing, text analysis, and medical diagnostics [3]. Central to this success are Deep Neural Networks (DNNs) [4], which efficiently process extensive data. Despite these achievements, DL systems face criticism for opacity and complexity, complicating validation and verification. Formal models [5] address these issues by offering structured mechanisms to analyze neural networks, improving robustness and interpretability. Unlike traditional methods, formal models provide rigorous approaches to assess DNN performance and efficiency, crucial in critical sectors like healthcare, automotive, and security [6].

This study examines the evolution of research on formal models applied to DL through a bibliometric analysis [7], focusing on trends, collaborations, and publication impact. It identifies key contributions and highlights research gaps in this expanding field. The research questions are:

1. How has research on formal models in Deep Learning evolved in terms of annual scientific growth and contributing countries?
2. Who are the most influential authors in this field, and which institutions produce the most work?
3. What are the most frequent keywords and the main trends of recent years?
4. How do collaborations between authors take place?

The paper is structured as follows: Section 2 presents the key concepts of DL, Section 3 describes the bibliometric analysis, followed by a comparative analysis in Section 4. Section 5 concludes with insights and future research avenues.

TACC'2024The 4th Tunisian-Algerian Conference on applied Computing, December 17-18, 2024, Constantine, Algeria
*Corresponding author.
anghamboukhari@fsegs.u-sfax.tn (A. Boukhari); aicha.choutri@univ-constantine2.dz (A. Choutri); faiza.belala@univ-constantine2.dz (F. Belala); ahmed.hadjkacem@fsegs.usf.tn (A. H. Kacem); riad.helal@univ-constantine2.dz (R. Helal)

2. Formal Models in Deep Learning: Bibliometric Analysis

2.1. Definitions

Formal models are mathematical frameworks used to rigorously describe and analyze systems to ensure their correctness and reliability. In the context of DNN and DL, formal models are increasingly applied to address challenges related to robustness, interpretability, and safety. These models are used for tasks such as probabilistic models, graphical models, and logic-based models, each of which serves distinct purposes.

1. Probabilistic Models: These models, particularly Bayesian networks and other probabilistic graphical models, are used to represent uncertainty and complex dependencies in deep learning tasks. Methods like variational inference and Monte Carlo enhance model robustness and generalization, especially by integrating probabilistic reasoning into neural networks [8].

2. Graphical Models: including Markov Random Fields (MRFs) and Hidden Markov Models (HMMs) are crucial for structured prediction tasks like image segmentation and sequence labeling. They enable neural networks to manage relationships between random variables, enhancing their handling of structured data and complex dependencies [8]

3. Logic-based models: refer to formal approaches that utilize logical systems to represent and analyze complex interactions among components. These models facilitate the simulation and prediction of signaling network behavior based on logical rules rather than traditional mathematical equations [9].

Formal models in DL enhance the robustness, interpretability, and reliability of neural networks across various applications. They employ probabilistic and logic-based methods to validate models, assess behavior, and quantify prediction uncertainties while ensuring adherence to safety constraints. These models are crucial for decision-making tasks in robotics and autonomous systems, helping handle diverse data sources and improving generalization across different use cases, especially in safety-critical domains like autonomous vehicles and healthcare.

2.2. Recent Advances

Data Sources: Scopus has become a leading bibliometric database, offering extensive coverage across disciplines and superior citation tracking—approximately 20 % more than Web of Science [10]. Its advanced analytical tools and consistent citation data outperform free databases like Google Scholar, PubMed, Dimensions, and Lens.org, which often lack complete metadata [11, 12, 13]. Scopus also provides detailed metadata, including citation networks, author information, and article references, and is regularly updated to include the latest publications. These features make it indispensable for rigorous bibliometric analyses and high-quality academic research [14].

2.3. Search Strategy

To gather recent publications on deep learning, formal models, and neural networks, we used the Scopus indexing database, renowned for its broad academic coverage. The search terms aligned with the study's objectives, targeting research that integrates deep learning, formal models, and performance evaluation. The query executed was: ("Deep Learning" OR "DL") AND ("Deep Neural Network*" OR "DNN*") AND (("Performance") OR ("Formal Models" AND ("Formal analysis" OR "Formal Verification"))), yielding 16,207 documents across 46 columns.

Filters ensured relevance and novelty by limiting the period to 2017–2024 and including all subject areas to capture interdisciplinary contributions. Only peer-reviewed articles and journals in English were considered to maintain reliability and comparability, given that around 80% of academic articles are published in English, which dominates global research trends. Scopus's focus on English further ensured uniformity and accessibility.

The database was processed using a Python script [15]. Certain columns with irrelevant metadata were removed, including 'Molecular Sequence Numbers', 'Chemicals/CAS', 'Tradenames', 'Manufacturers', 'Funding Details', 'Editors', 'Sponsors', 'Conference name', 'Conference date', 'Conference location', 'Conference code', 'ISBN'. The 'Molecular Sequence Numbers' column, for instance, was excluded as it did not contribute meaningful information to the analysis of trends in formal models applied to deep learning. Missing values were addressed by filling them in where feasible, and columns with over 90% missing values were eliminated. Duplicates were identified by title or DOI and removed. After cleaning, the dataset contained 16,205 documents across 34 columns.

Subsequently, we analyzed publication trends to track the evolution of interest in formal models and deep learning. We identified influential authors, examined collaboration networks, and highlighted key research groups and contributors.

2.4. Data Analysis

The data was processed using a Python script, which played a crucial role in conducting the analysis by taking the collected data as input and leveraging various libraries and functions to facilitate data processing and preparation. Subsequently, the analyses were performed using R software, specifically with the *Bibliometrix* and *Biblioshiny* packages [16]. These analyses allowed for a comprehensive examination of various aspects, including the evolution of scientific production in the field, identification of the most frequently cited articles, and recognition of the most influential authors and their main contributions. Additionally, the analysis explored the geographic distribution of prolific authors and highlighted the contributions and relative impact of different countries. The study further identified the most active and highly cited research institutions across the dataset, providing valuable insights into collaborative networks within the field. Moreover, the analysis mapped the key partnerships and central hubs of the global research network.

3. Comparative Analysis

3.1. Annual Scientific Production

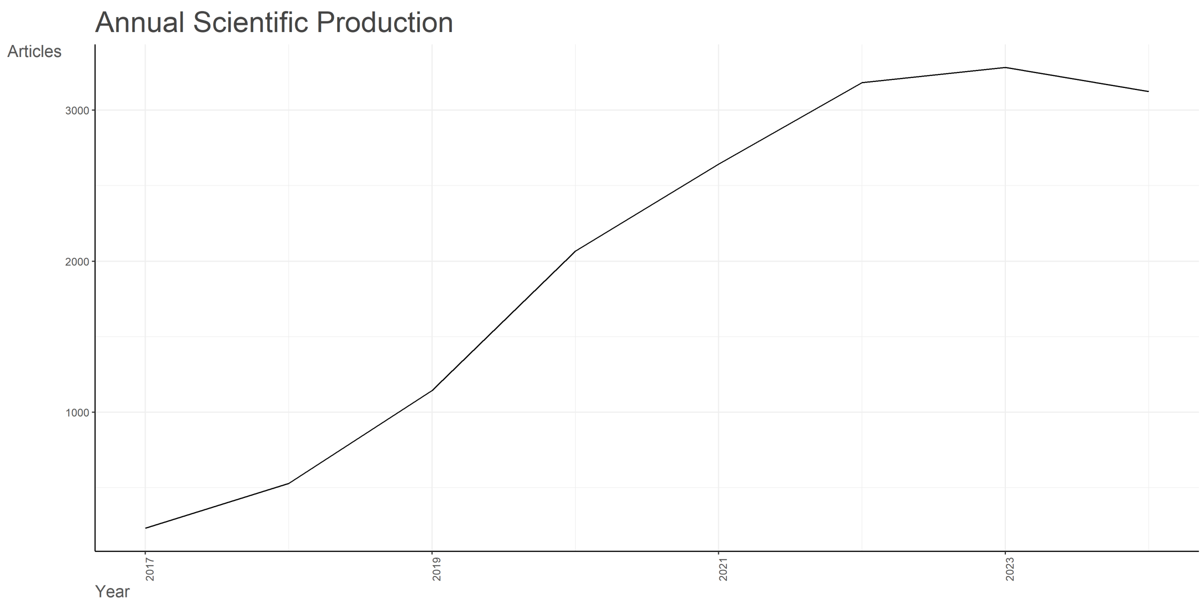

Figure 1: Annual scientific production from 2017 to 2024

The graph in figure 1 shows a significant increase in scientific production in the field of formal models applied to DNN and DL between 2017 and 2023, with an estimate for 2024. The growth is particularly notable between 2017 and 2021, rising from 231 to 2,643 articles, reflecting a growing interest in this expanding field. From 2021 to 2023, the number of publications stabilizes around 3,200 articles, with a peak in 2023 at 3,283 articles. This stabilization suggests a certain maturity in the field, although

Table 1
Top 10 Most Cited Articles

Ref.	[17]	[18]	[19]	[20]	[21]	[22]	[23]	[24]	[25]	[26]
Cit.	14405	7105	6169	4095	3289	2574	2117	2055	1782	1769

the estimate for 2024 (3,125 articles) indicates a slight decline. This could point to a temporary shift in focus towards other subfields or a minor decrease in activity within the domain. Overall, the trend highlights that formal models are playing an increasingly important role in improving performance and verifying neural networks, particularly in critical applications. In total, the dataset includes 16,205 publications, underscoring the substantial volume of research dedicated to this area over the past years. Table 1 highlights the top 10 most cited articles related to the specified topic, selected from a total of 16,205 records in the dataset:

3.2. Most relevant Authors

The diagram presented in Figure 2 shows that Zhang Y, Wang Y, and Li Y are the most prolific authors in the field of DNN and DL, each having published over 300 articles, likely on topics such as DNN architectures and optimization methods. Other authors, such as Wang J, Li X, and Wang X, also contribute significantly with 200 to 250 publications. The strong presence of Chinese researchers with similar names may indicate potential collaborations. Their work covers various aspects, revealing trends such as the improvement of DNN performance and the exploration of unsupervised learning.

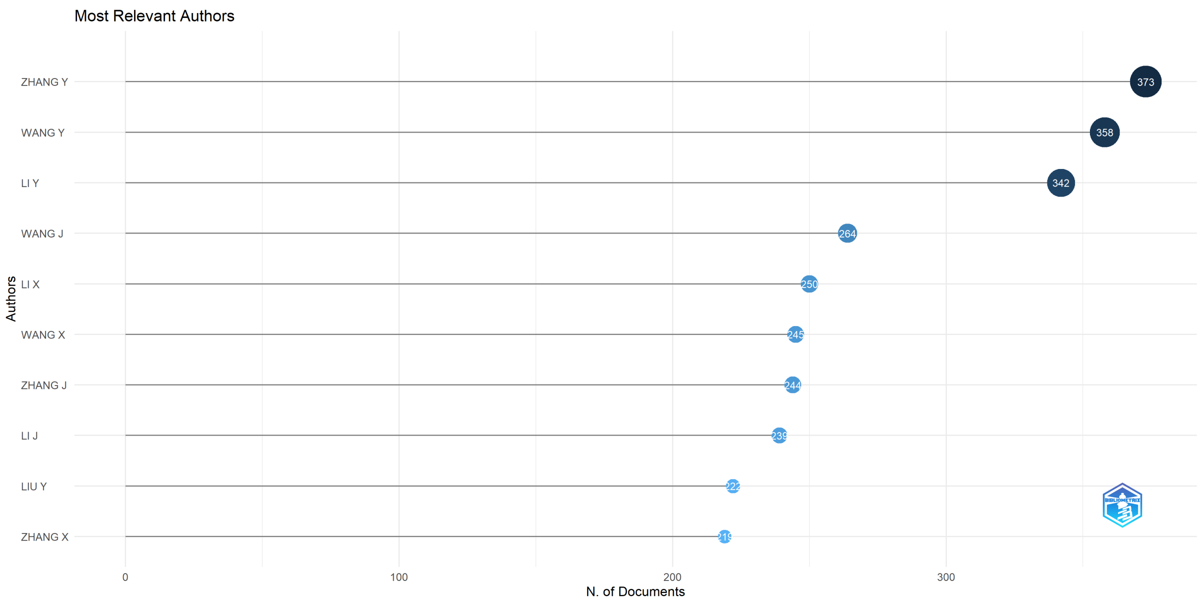

Figure 2: Most Relevant Authors

3.3. Authors' Production over Time

The chart in figure 3 illustrates the scientific output of the top ten authors working on the application of formal models to DNN from 2017 to 2024. Certain authors, such as Wang X and Zhang J, stand out for their particularly high productivity and significant recognition of their work, as shown by the numerous citations they receive. Wang X, for instance, experienced a major peak in 2021, suggesting a key contribution during that period. Other authors, like Li Y and Zhang Y, show more modest output, possibly indicating specialization in specific subfields. Overall, the consistent scientific output in this area reflects the ongoing growth of research on DNNs, highlighting the importance of these authors' contributions to developing robust and reliable methods for these technologies. Their work has a significant influence on the community, and the field is rapidly expanding with continuous innovations.

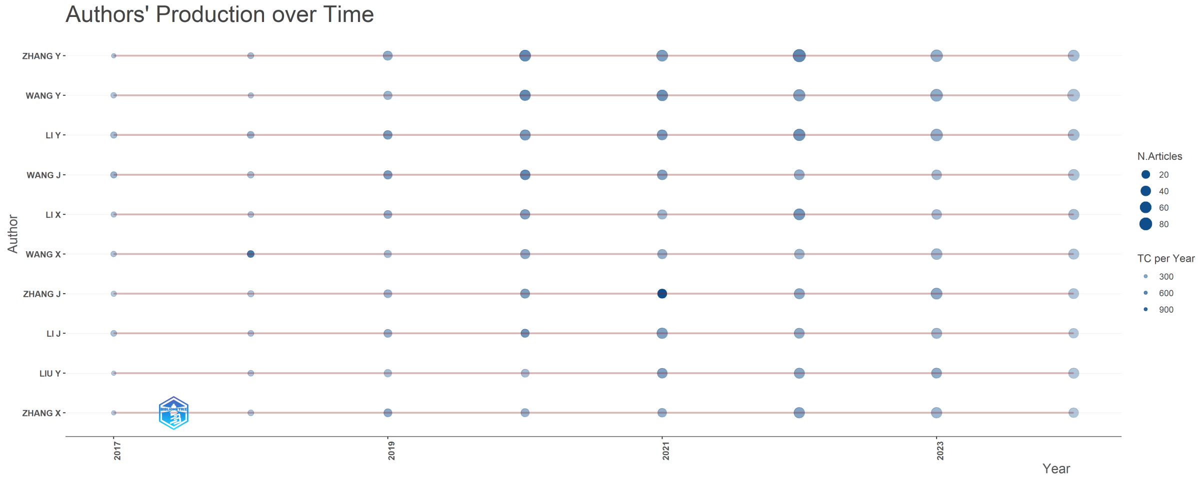

Figure 3: Top 10 Authors' production over time

3.4. High-Frequency Terms

Table 2 showcases the most frequently used keywords by the authors, providing insight into the main research themes and trends within the field.

Table 2
Most Frequent Words in the Corpus

Words	Occurrences
deep learning	12903
deep neural networks	12219
convolution neural networks	5065
convolution	3899
convolution neural networks	3601
learning systems	3330
article	3324
human	3269
deep neural network	2225
machine learning	2129

3.5. Words' Frequency over Time

In this comprehensive analysis, our main objective was to study the changing trends in interest in DL-related topics by ranking keyword frequencies by year. Notably, "deep learning" emerged as the predominant keyword, although it was intentionally excluded from the main objective of this study. Our aim was to shed light on other keywords associated with it. For a detailed analysis of our results, please refer to Figure 4 for the revealed results.

3.6. Leading Affiliations

The analysis in Figure 5 highlights the most relevant university affiliations in terms of scientific output. Tsinghua University leads with 550 articles, followed by Zhejiang University with 513. These two institutions clearly dominate research production. Next are the University of Electronic Science and Technology of China and Xidian University, with 452 and 441 articles, respectively. Other universities,

Year	DEEP LEARNING	DEEP NEURAL NETWORKS	CONVOLUTIONAL NEURAL NETWORK	CONVOLUTION	CONVOLUTIONAL NEURAL NETWORKS	LEARNING SYSTEMS	ARTICLE	HUMAN	DEEP NEURAL NETWORK	MACHINE LEARNING
2017	202	205	108	92	14	71	43	47	11	80
2018	586	642	272	260	37	171	155	166	21	180
2019	1557	1585	744	646	109	285	412	416	74	386
2020	3483	3200	1208	1155	671	817	892	855	366	638
2021	5733	5140	1740	1608	1306	1401	1482	1445	759	928
2022	8092	7565	2838	2448	2133	1835	2052	2056	1188	1321
2023	10439	9974	3984	3257	2875	2655	2697	2664	1710	1693
2024	12897	12219	5065	3899	3601	3330	3324	3269	2224	2128

Figure 4: Keyword Frequency Trends Over Time

such as Huazhong, Shanghai Jiao Tong, and Wuhan, also stand out with between 392 and 426 articles. Lastly, Beihang, Southeast, and Sichuan universities round out the list, each contributing around 350 articles. The data emphasizes how scientific output is concentrated in a few dominant universities.

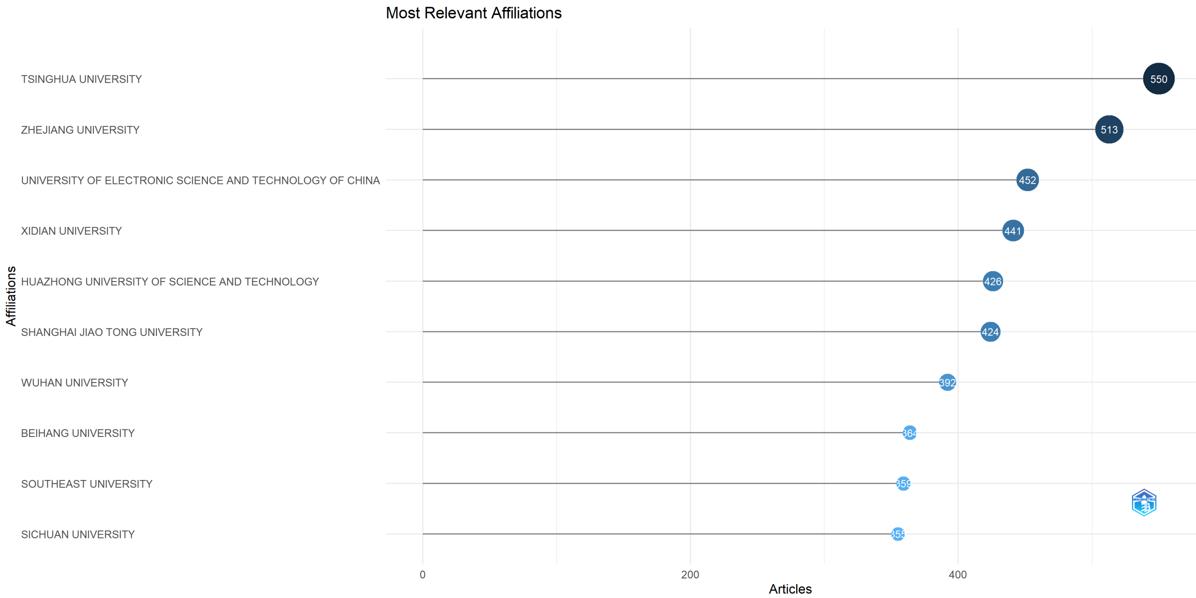

Figure 5: Leading University Affiliations by Scientific Output

3.7. Country Distribution of Authors

Figure 6 shows the distribution of corresponding authors' countries in publications on DNN and DL. China dominates with a high number of publications from single-country collaborations (SCP), followed by India and the United States. Countries like Germany, Iran, and France are more involved in multi-country collaborations (MCP), but their overall volume is lower. This reflects a significant research dynamic in China and India, with a predominance of national publications.

3.8. Trend topics

The analysis presented in image 7 highlights the rise of Transformers, particularly after 2021, in natural language processing and machine learning. Contrastive learning is also becoming a major topic, reducing reliance on labeled data and improving model efficiency, especially in computer vision. The use of large datasets is rapidly expanding, but it poses challenges in terms of management and energy efficiency. While convolutional neural networks (CNNs) remain relevant, Transformers appear to outperform them in several tasks. Finally, a focus on integrating CNNs and Transformers, as well as optimizing performance while minimizing environmental impact, could be key moving forward.

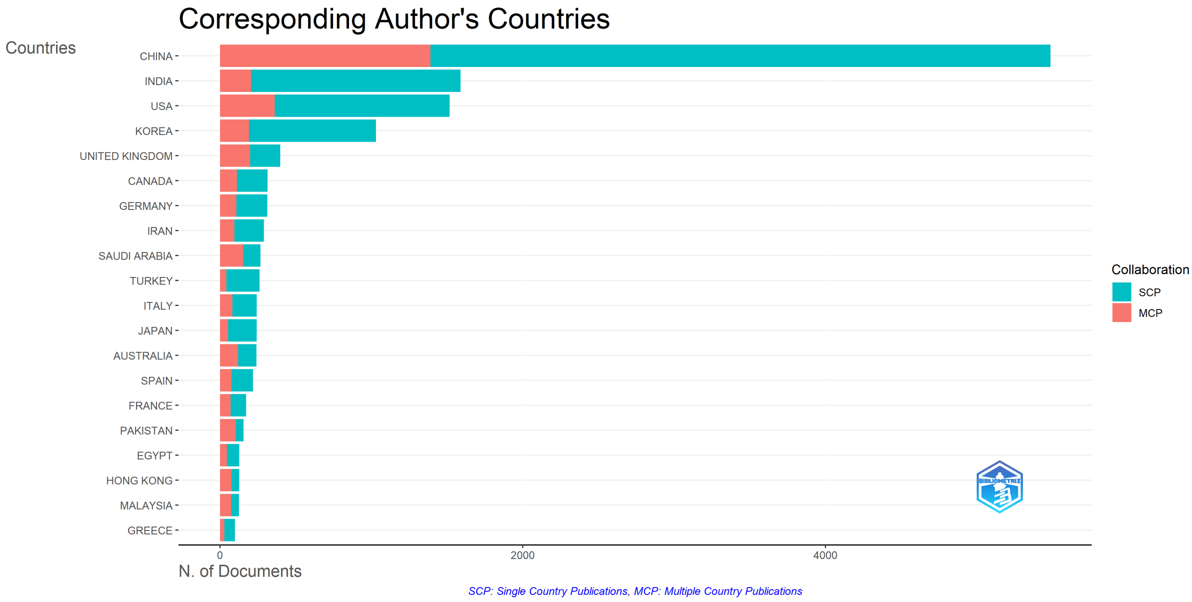

Figure 6: Corresponding Authors by Country

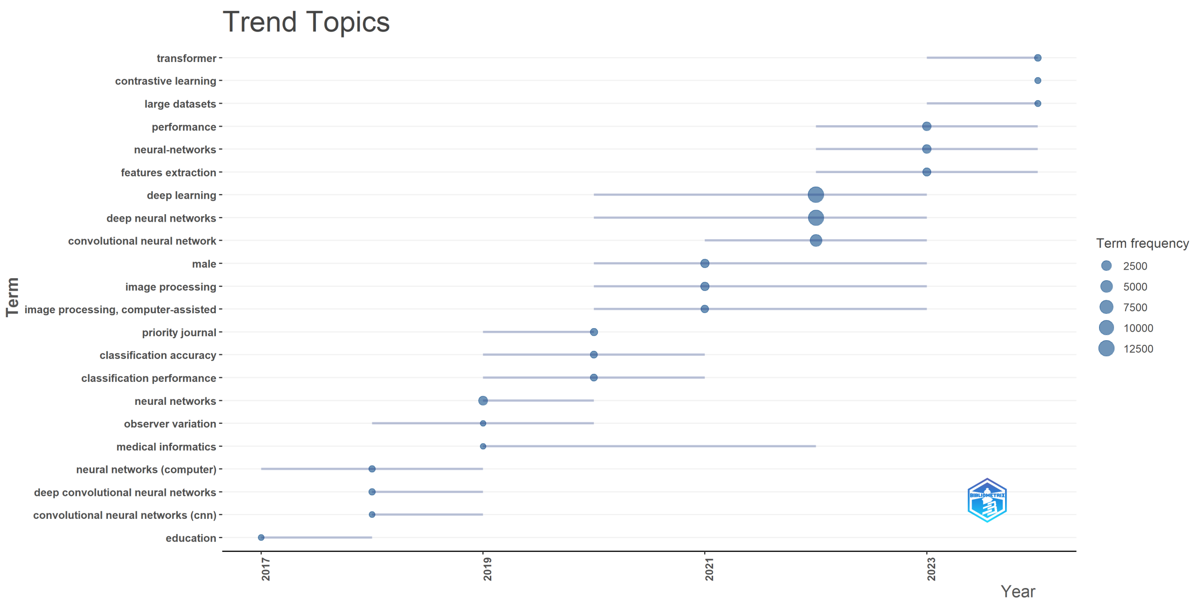

Figure 7: Analysis of trend topics

3.9. Collaboration Network

This graph (Figure 8) presents the final output of the collaboration network analysis conducted in R using the Biblioshiny tool. The network reveals a core-periphery structure, where authors like "Zhang Y," "Wang Y," and "Li J" act as central "hubs" with numerous connections, indicating their prominence in the field. Meanwhile, a small isolated group, represented in red, is disconnected from the main network. This visualization captures the dynamics of scientific collaboration, with a dense core of highly interconnected researchers surrounded by peripheral, less-connected authors. Common names, such as "Wang" and "Li," posed challenges in distinguishing individual authors, but the structure still provides valuable insights into collaborative relationships. Due to the dataset's large size, it could not be imported into VOSviewer, highlighting Biblioshiny's effectiveness in handling extensive data for visualizations like this.

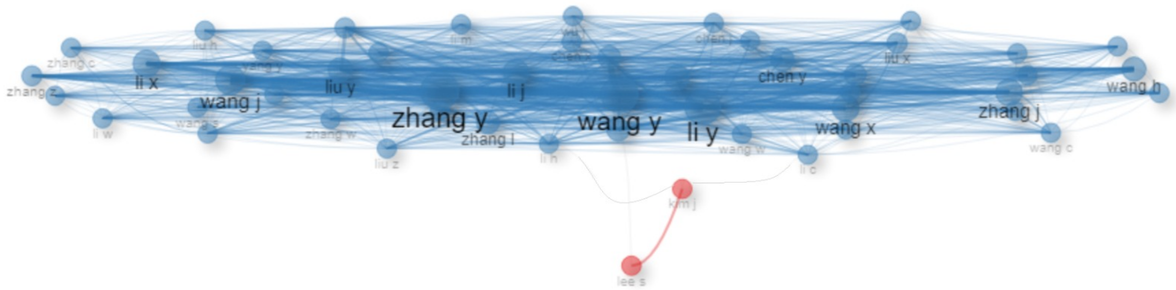

Figure 8: Collaboration Network

3.10. Comparison with Existing Studies

Our findings align with previous studies highlighting the growing importance of formal models in enhancing the robustness, interpretability, and safety of deep learning (DL) systems, particularly in fields such as healthcare and autonomous systems. For instance, the work by Chen et al. (2018), which developed the DeepLab model for semantic segmentation, demonstrates how the use of atrous convolution improves spatial accuracy [17]. Furthermore, their research highlights significant advances in the ability of models to extract fine details without substantially increasing the number of parameters. In contrast to these approaches, our analysis shows that the integration of formal models not only improves this accuracy but also strengthens the robustness of the systems. The work of Shorten et al. (2019) on data augmentation, notably through the use of GANs, confirms the importance of adopting sophisticated strategies to ensure model generalizability [18]. Similarly, Zhang et al. (2017), with their DnCNN model for image denoising, emphasize the effectiveness of residual techniques in improving network performance [19]. Moreover, the evolution of CNN architectures towards deeper networks, as shown by Gu et al. (2018) with ResNet, addresses gradient issues effectively, supporting our observations on the impact of residual connections [20]. Additionally, Alzubaidi et al. (2021) highlighted the dominance of modern CNN architectures in complex applications [21]. Our study extends this analysis by demonstrating the importance of formal models in various contexts. Kamnitsas et al. (2017) introduced a multi-scale 3D CNN model for brain lesion segmentation, illustrating the importance of multi-scale contexts [22]. This approach supports our analysis, which integrates contextual information to enhance precision. Finally, Hannun et al. (2019) proved the effectiveness of deep neural networks (DNN) in arrhythmia classification with a high AUC score [26]. Our study also supports this approach by emphasizing how formal models can enhance predictive performance in critical medical applications.

4. Discussion

4.1. Results

The research questions outlined in the introduction have been thoroughly explored through the study's findings. Below is an analysis linking each question with its respective answer:

Q1: How has research on formal models in Deep Learning evolved in terms of annual scientific growth and contributing countries?

R1: Research on formal models within the deep learning domain has shown substantial growth, particularly between 2017 and 2021, indicating increased global attention. By 2023, a phase of stabilization occurred, pointing to the field's maturity and the necessity for innovative directions or emerging subfields to catalyze further advancements. Leading contributors include China, the U.S., and key European nations, reflecting considerable research funding and focus in these regions.

Q2: Who are the most influential authors in this field, and which institutions produce the most work?

R2: Influential figures such as Zhang Y., Wang Y., and Li Y. have made significant and consistent contributions. Institutions like Tsinghua University and Zhejiang University are notable for their prolific output and extensive research partnerships, enhancing their strong positions within the field.

This highlights their leadership in producing impactful research and fostering influential academic collaborations.

Q3: What are the most frequent keywords and main trends of recent years?
R3: Commonly recurring terms include "Deep Learning" and "Deep Neural Networks," which continue to dominate the landscape. However, there has been an increased emphasis on emerging keywords such as "transformers" and "contrastive learning," highlighting new strategies for handling large datasets and improving model performance. Transformers, with their attention mechanism, allow parallel sequence processing, enhancing speed and efficiency, especially in NLP tasks like translation [27]. This innovation extends to fields such as computer vision. Contrastive learning improves data representation and model generalization without needing extensive labeled data, reflecting the field's adaptation to technological challenges [28].

Q4: How do collaborations between authors take place?
R4: Author collaborations tend to be predominantly national, with a strong concentration in China, illustrating a focus on bolstering domestic research networks. This shift from earlier, broader international collaborations indicates a strategic emphasis on regional research independence and focus.

4.2. Biases and Limitations

Several obstacles have impacted the quality of our analysis. While the Scopus database is comprehensive and widely recognized, it has inherent limitations. For instance, it may not encompass all relevant publications, particularly those in emerging or niche journals, leading to selection bias and limited coverage diversity. Additionally, comparisons with other databases like Web of Science and Google Scholar reveal that Scopus may prioritize specific fields, potentially skewing research findings. Keyword-based search strategies may exclude pertinent studies that use different terminologies, introducing language bias and restricting analysis scope. Moreover, unintended biases in interpreting results should be considered. Emphasizing specific emerging keywords might highlight current trends but not fully represent the broader academic landscape. Despite measures taken to minimize these biases, they can affect the generalizability and robustness of conclusions. A broader analysis involving multiple databases and more inclusive search strategies could help mitigate these limitations.

5. Conclusion

Formal models applied to Deep Learning (DL) and Deep Neural Networks (DNN) have gained significant attention in recent years for their potential to enhance system robustness, interpretability, and reliability. Given the wide range of applications and the rapid pace of technological progress in this field, it can be challenging to cover these developments comprehensively through traditional narrative reviews.

Our bibliometric analysis provides a detailed overview of the evolution of publications on formal models in DL, highlighting their contributions to system validation and performance improvement. Leveraging Python for data extraction and processing, and R with the *Bibliometrix* package for analysis, we visualized key trends, collaborative networks, and the influence of major contributors in the field. This approach offers a holistic view of the landscape and identifies critical research hubs and influential authors.

In light of the growing significance of formal models, we recommend that future research continues to explore this domain, with particular focus on interdisciplinary approaches. Emerging techniques, such as transformers and contrastive learning, present promising opportunities to address current challenges, including enhanced model validation and energy efficiency. Future studies should investigate how formal models can integrate with these methods to boost robustness and performance, particularly in critical fields like healthcare and autonomous systems.

Acknowledgment

This work was partially supported by the LABEX-TA project MeFoGL: "Méthode Formelles pour le Génie Logiciel"

Declaration on Generative AI

During the preparation of this work, the authors used ChatGPT and DeepL Writer in order to: Perform grammar and spelling checks. Further, the authors reviewed and edited the content as needed and takes full responsibility for the publication's content.

References

[1] H. Wang, B. Raj, On the origin of deep learning, arXiv preprint arXiv:1702.07800 (2017).
[2] P. R. Kumar, E. B. K. Manash, Deep learning: A branch of machine learning, in: Journal of Physics: Conference Series, volume 1228, IOP Publishing, 2019, p. 012045.
[3] W. G. Hatcher, W. Yu, A survey of deep learning: Platforms, applications and emerging research trends, IEEE access 6 (2018) 24411–24432.
[4] R. Miikkulainen, J. Liang, E. Meyerson, A. Rawal, D. Fink, O. Francon, B. Raju, H. Shahrzad, A. Navruzyan, N. Duffy, et al., Evolving deep neural networks, in: Artificial intelligence in the age of neural networks and brain computing, Elsevier, 2024, pp. 269–287.
[5] Z. Feng, Formal Models of Neural Network and Deep Learning, Springer Nature Singapore, Singapore, 2023, pp. 653–752. URL: https://doi.org/10.1007/978-981-16-5172-4_11. doi:10.1007/978-981-16-5172-4_11.
[6] D. Corsi, E. Marchesini, A. Farinelli, Formal verification of neural networks for safety-critical tasks in deep reinforcement learning, in: Uncertainty in Artificial Intelligence, PMLR, 2021, pp. 333–343.
[7] I. Passas, Bibliometric analysis: the main steps, Encyclopedia 4 (2024).
[8] H.-C. Crayencour, C.-E. Cella, Learning, probability and logic: Toward a unified approach for content-based music information retrieval, Frontiers in Digital Humanities 6 (2019) 6.
[9] M. K. Morris, J. Saez-Rodriguez, P. K. Sorger, D. A. Lauffenburger, Logic-based models for the analysis of cell signaling networks, Biochemistry 49 (2010) 3216–3224.
[10] C. Analytics, Web of science, 2020.
[11] A. Martín-Martín, R. Costas, T. Van Leeuwen, E. D. López-Cózar, Evidence of open access of scientific publications in google scholar: A large-scale analysis, Journal of informetrics 12 (2018) 819–841.
[12] R. W. Mouratidis, Dimensions, Journal of the Medical Library Association: JMLA 107 (2019) 459.
[13] S. McReynolds, Research Guides: Lens Guide: How to Use Lens.org, ???? URL: https://researchguides.library.syr.edu/lensguide/use.
[14] M. E. Falagas, E. I. Pitsouni, G. A. Malietzis, G. Pappas, Comparison of pubmed, scopus, web of science, and google scholar: strengths and weaknesses, The FASEB journal 22 (2008) 338–342.
[15] Z. Dobesova, Programming language python for data processing, in: 2011 International Conference on Electrical and Control Engineering, IEEE, 2011, pp. 4866–4869.
[16] S. Büyükkıdık, A bibliometric analysis: A tutorial for the bibliometrix package in r using irt literature, Journal of Measurement and Evaluation in Education and Psychology 13 (2022) 164–193.
[17] L.-C. Chen, G. Papandreou, I. Kokkinos, K. Murphy, A. L. Yuille, Deeplab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected crfs, IEEE Transactions on Pattern Analysis and Machine Intelligence 40 (2018) 834–848. doi:10.1109/TPAMI.2017.2699184.
[18] C. Shorten, T. M. Khoshgoftaar, A survey on image data augmentation for deep learning, Journal of big data 6 (2019) 1–48.
[19] K. Zhang, W. Zuo, Y. Chen, D. Meng, L. Zhang, Beyond a gaussian denoiser: Residual learning

of deep cnn for image denoising, IEEE Transactions on Image Processing 26 (2017) 3142–3155. doi:10.1109/TIP.2017.2662206.

[20] J. Gu, Z. Wang, J. Kuen, L. Ma, A. Shahroudy, B. Shuai, T. Liu, X. Wang, G. Wang, J. Cai, et al., Recent advances in convolutional neural networks, Pattern recognition 77 (2018) 354–377.

[21] L. Alzubaidi, J. Zhang, A. J. Humaidi, A. Al-Dujaili, Y. Duan, O. Al-Shamma, J. Santamaría, M. A. Fadhel, M. Al-Amidie, L. Farhan, Review of deep learning: concepts, cnn architectures, challenges, applications, future directions, Journal of big Data 8 (2021) 1–74.

[22] K. Kamnitsas, C. Ledig, V. F. Newcombe, J. P. Simpson, A. D. Kane, D. K. Menon, D. Rueckert, B. Glocker, Efficient multi-scale 3d cnn with fully connected crf for accurate brain lesion segmentation, Medical image analysis 36 (2017) 61–78.

[23] A. Mathis, P. Mamidanna, K. M. Cury, T. Abe, V. N. Murthy, M. W. Mathis, M. Bethge, Deeplabcut: markerless pose estimation of user-defined body parts with deep learning, Nature neuroscience 21 (2018) 1281–1289.

[24] H. Ismail Fawaz, G. Forestier, J. Weber, L. Idoumghar, P.-A. Muller, Deep learning for time series classification: a review, Data mining and knowledge discovery 33 (2019) 917–963.

[25] A. Khan, A. Sohail, U. Zahoora, A. S. Qureshi, A survey of the recent architectures of deep convolutional neural networks, Artificial intelligence review 53 (2020) 5455–5516.

[26] A. Y. Hannun, P. Rajpurkar, M. Haghpanahi, G. H. Tison, C. Bourn, M. P. Turakhia, A. Y. Ng, Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network, Nature medicine 25 (2019) 65–69.

[27] R. Hanslo, Deep learning transformer architecture for named-entity recognition on low-resourced languages: State of the art results, in: 2022 17th Conference on Computer Science and Intelligence Systems (FedCSIS), IEEE, 2022, pp. 53–60.

[28] C.-Y. Chuang, J. Robinson, Y.-C. Lin, A. Torralba, S. Jegelka, Debiased contrastive learning, Advances in neural information processing systems 33 (2020) 8765–8775.