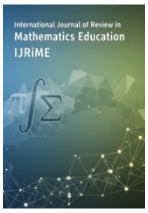

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Evolution of Deep Learning and Its Reflection on Statistical Mathematics Learning

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Abstract

This study aims to evaluate the development, topic interconnections, and global research directions in the field of Deep Learning during the period 2019–2024, while also examining its implications for teaching statistical mathematics in the digital era. A bibliometric approach was used to analyze publication trends, citation patterns, and keyword relationships with the assistance of VOSviewer software. Data were obtained from the Scopus database using the main keywords “Deep Learning,” “Neural Networks,” and “Artificial Intelligence.” The results indicate that peak research activity occurred in 2022 with a significant surge in citations, followed by a decline in 2023–2024, marking a phase of research stabilization. Network analysis revealed that topics such as computer vision, medical imaging, and unsupervised learning dominate, while emerging trends like federated learning and edge computing are beginning to develop toward privacy and computational efficiency. Geographically, the United States and China are the main contributors to scientific publications, followed by Germany, the United Kingdom, and Australia. These findings highlight that the core success of Deep Learning is fundamentally grounded in statistical mathematics, particularly in optimization and probabilistic modeling. Accordingly, the implications for teaching statistical mathematics involve reorienting curricula toward applied, data-driven contexts emphasizing probabilistic thinking, algorithmic reasoning, and the integration of computational tools. Such an approach encourages students to bridge theoretical understanding with real-world problem solving in artificial intelligence and data science.

Keywords: Deep Learning, Bibliometric, Statistical Mathematics, Artificial Intelligence

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1. Introduction

The rapid advancement of digital technology in the 21st century has transformed how humans process, interpret, and utilize data. Among these technological innovations, Deep Learning (DL) a branch of Artificial Intelligence (AI) that simulates neural information processing has become one of the most influential paradigms in modern computation (Apriadi et al., 2025). DL has demonstrated remarkable performance in various domains, including computer vision, natural language processing, and medical diagnostics. Beneath this success lies a strong foundation in statistical mathematics, encompassing optimization, regression, probability theory, and distribution analysis (Nurazizah & Jana, 2022). Hence, understanding these mathematical principles is critical not only for advancing DL research but also for rethinking how statistical concepts are taught in higher education.

Despite its growing influence, statistics education often remains dominated by formulaic computation and theoretical proofs, with limited emphasis on data interpretation and model-based reasoning. This creates a pedagogical gap between the abstract nature of traditional statistics teaching and the data-driven, algorithmic reasoning required in modern AI applications. Students frequently struggle to connect probabilistic theory with real-world data analysis or algorithmic modeling (Abdussamad, 2025 ; Marhawati et al., 2022). As a result, there is a pressing need to redefine the role of statistical mathematics education so that it aligns with the analytical thinking demanded in the era of artificial intelligence and big data.

Deep Learning represents an intersection where computational efficiency meets statistical reasoning. However, while DL's mathematical foundations are well acknowledged, there is limited understanding of how current global research trends in DL reflect shifts in the underlying statistical thinking that could inform educational innovation. To bridge this gap, it is essential to explore the evolution of DL research topics and their interconnections with statistical principles to derive actionable insights for the teaching and learning of statistical mathematics.

Accordingly, this study employs a bibliometric and research trend analysis to map the global development of Deep Learning research from 2019 to 2024. The bibliometric method enables a quantitative synthesis of publication patterns, keyword interrelations, and thematic evolution, thereby revealing how the intellectual structure of DL has evolved. Through this lens, the study not only describes research dynamics such as leading countries, topics, and citation patterns but also seeks to interpret how these developments imply a paradigm shift in the teaching of statistical mathematics toward integrative, application-oriented, and conceptually grounded approaches.

Therefore, this study aims to answer three main questions:

a. What are the key publication and citation trends in Deep Learning research between 2019 and 2024?
b. How are research topics and clusters within DL interconnected, particularly in relation to statistical concepts such as optimization and probabilistic modeling?
c. How can these evolving research directions inform and inspire the restructuring of statistical mathematics curricula to better prepare students for the challenges of the digital and AI-driven era?

2. Method/Approach

This study employed a bibliometric approach and research trend analysis to evaluate the development, topic interconnections, and research directions in the field of Deep Learning (DL) during the period 2019–2024. The bibliometric approach was chosen because it allows for a quantitative mapping of the intellectual structure and evolution of scientific knowledge through publication metadata (Aria & & Cuccurullo, 2017). This research adopts a descriptive-quantitative design, focusing on identifying temporal publication trends, topic interrelationships, and geographical or institutional contributions to the global development of DL research (Tekdal, 2021 ; Van Eck & Waltman, 2010).

Data Source and Search Strategy: All data were retrieved from the Scopus database on September 15, 2024. The inclusion criteria comprised (a) journal articles, conference proceedings, and literature reviews; (b) documents published in English between 2019 and 2024; and (c) works relevant to computer science, engineering, and medical informatics. Exclusion criteria included editorials, notes, non-English publications, and papers without sufficient metadata (e.g., missing author affiliation or keywords).

Data Extraction and Preprocessing: Metadata such as titles, authors, affiliations, keywords, publication years, countries of origin, and citation counts were exported in CSV format for analysis. A systematic data cleaning process was conducted to ensure data consistency and validity. Duplicate records were removed, keyword synonyms were merged (e.g., "DL" with "Deep Learning," "DNN" with "Deep Neural Networks"), and inconsistent spellings were standardized following the guidelines of bibliometric data normalization (Creswell, 2019). Non-relevant keywords (e.g., "COVID-19," "COVID," "SARS-CoV-2") were excluded after manual inspection since they represented contextual but not conceptual overlaps with DL research.

Data Analysis and Visualization: Data analysis was carried out using VOSviewer version 1.6.19 for co-occurrence, co-authorship, and citation network analyses. The analysis consisted of three stages: 1. Publication and citation trend analysis to track annual research output and citation dynamics. 2. Keyword co-occurrence and clustering analysis to identify dominant thematic clusters and conceptual interconnections (e.g., computer vision, medical imaging, unsupervised learning, federated learning). 3. Overlay and density visualization to observe temporal topic shifts and research intensity through color-coded gradients. 4. While VOSviewer was used for its strengths in mapping bibliometric networks and visualizing conceptual relationships, the authors acknowledge that it has limitations in performing advanced statistical modeling. Therefore, the study focuses primarily on descriptive mapping rather than inferential bibliometric statistics. Future studies could complement this approach with Biblioshiny (R-based) or SciMAT to extend collaboration and thematic evolution analyses (Donthu et al., 2021 ; Crismono, 2024).

Ethical and Pedagogical Considerations: Although bibliometric data are secondary and publicly accessible, the analysis was conducted in compliance with Scopus data usage guidelines. The methodological framework is designed not only to quantify research dynamics but also to extract conceptual insights relevant to the teaching of statistical mathematics, linking the evolution of DL research topics with pedagogical implications for data literacy, probabilistic reasoning, and applied modeling in higher education.In addition, an analysis of geographical and institutional contributions was also conducted by observing the distribution of publications based on the authors' countries and affiliations. This data was visualized in the form of world maps and bar charts to identify the most influential countries and institutions in Deep Learning research. The validity of the analysis was reinforced through triangulation of results between VOSviewer and Bibliometrix to ensure more accurate data interpretation. Each resulting thematic cluster was then interpreted based on supporting literature to understand the direction of development and potential collaboration among research fields. Thus, this research method not only describes trends and the scientific structure in the field of Deep Learning, but

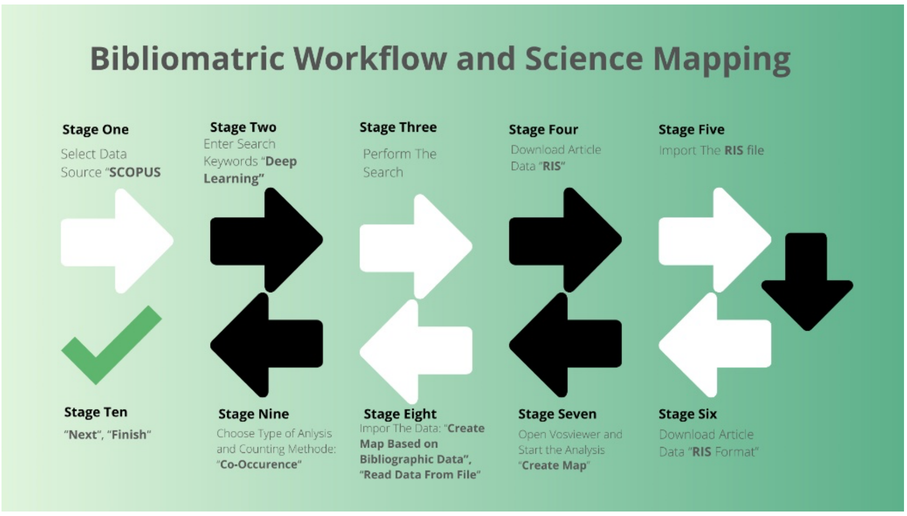

Figure 1. Bibliometric Workflow

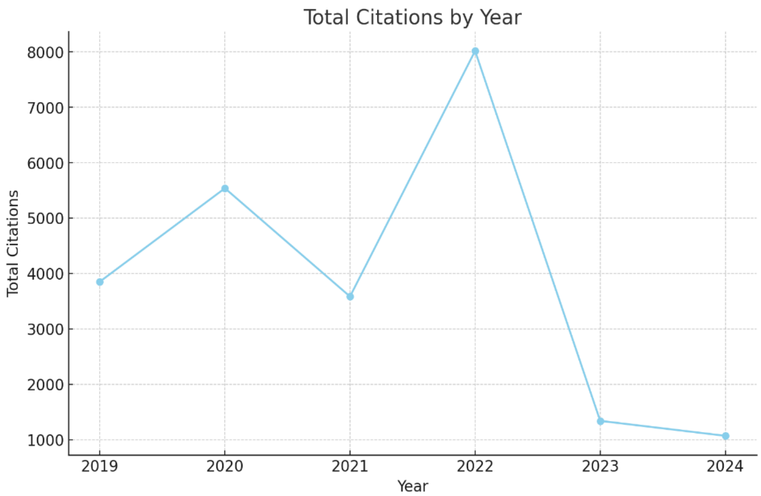

Figure 2. Citation Trends Over the Years

also provides an empirical basis for understanding the evolution of knowledge and the future direction of artificial intelligence research development.

Settings and downloading Publish or Perish up to importing and settings and VOSviewer data on figure 1.

3. Result and Discussion

Result

a. Citation Trends and development of academic interest in "Deep Learning"

This graph on figure 2 displays the trend pattern in the number of citations from 2019 to 2024. This trend provides insight into how Deep Learning research is gaining attention and relevance in academic or professional communities over time. In 2019, the number of citations started at around 4000, indicating that Deep Learning research has received significant attention in the academic community. This is most likely due to the increasingly widespread application of artificial intelligence technology in various sectors (Dong, 2020). In 2020, the number of citations increased to 5500, which could be due to the emergence of more relevant research

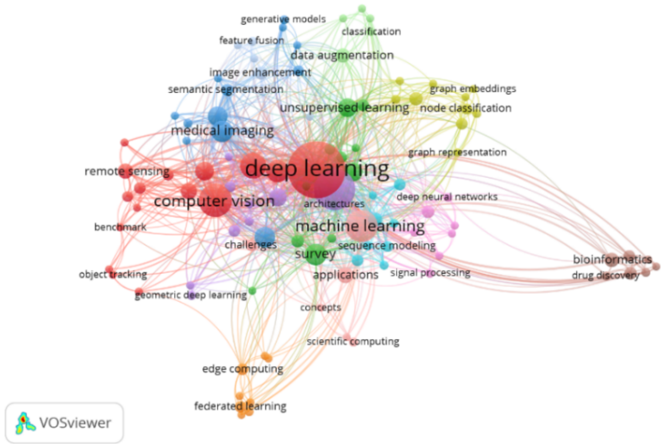

Figure 3. Network Visualization of Deep Learning and Related Research Themes

and the increasing number of publications that received widespread attention from researchers around the world. This growth indicates that Deep Learning is still a major focus in AI research, with many new innovations produced during the year (W. Wu, 2019).

In 2021, the number of citations decreased significantly to below 3500. This decrease could be caused by various factors, such as saturation in certain research, the emergence of new technologies that divert the attention of the research community, or a reduction in the number of fundamental research that attracts many citations (Buslaev, 2020). However, in 2022, there was a drastic jump in the number of citations reaching 8000, making it the year with the highest number of citations in this graph. This sharp increase can be attributed to major breakthroughs in the field of Deep Learning, such as the development of more sophisticated AI models, the increase in industrial applications using this technology, and increased investment in AI research and development by academic institutions and large technology companies (Pouyanfar, 2019).

After peaking in 2022, the number of citations experienced a very drastic decline in 2023, dropping to 1500 citations. This decline may be due to a decrease in publications gaining widespread acclaim, or a change in research trends towards other areas of AI, such as federated learning or more advanced generative AI. In 2024, the number of citations further decreases to close to 1000, which is the lowest point in the analyzed time period. This could mean that research in Deep Learning has reached a certain stage of maturity, where only major innovations are still receiving significant attention from the academic community.

Overall, this graph illustrates a common pattern for certain works, in which they gain a peak in popularity early in the period of publication, but that popularity cannot be maintained in the long term. While there have been some minor resurgences in certain years, the number of citations has generally shown a downward trend. This underlines the importance of the factors of relevance, innovation, and renewal in maintaining the attention of the academic or professional community to a work (Z. Wu, 2021).

b. Deep Learning Topic Network Visualization with VOSviewer

This visualization on figure 3 is a map of relationships or networks of relationships between research topics generated using VOSviewer. This map represents the relationships between various keywords or key topics that often appear in scientific publications, with a focus on "deep learning" as the main center. Each element in this map shows the thematic relationships between topics as well as their frequency and relevance in research. The keyword "deep learning" is at the center of visualization with the largest circle, indicating that this is the topic that comes up most often and is at the heart of various studies in this field. A strong link is seen between "deep learning" and several other topics such as "computer vision," "machine learning," and "medical imaging." These three topics are often mentioned in the context of the application of deep learning technology, which includes image analysis, data processing, and application (Liu, 2022).

In addition, topics such as "unsupervised learning" and "graph embeddings" are also emerging as important parts of this network. This indicates that the unsupervised learning approach and embedding-based graph representation are research areas that are closely related to deep learning methods, especially in processing complex data (Zhang, 2021). The red cluster is the main cluster centered on "deep learning" as the core. Topics such as "computer vision," "medical imaging," and "semantic segmentation" are included in this cluster. The focus of this cluster is on the application of deep learning technology in visual data analysis, such as medical image processing, object tracking, and image segmentation (Lei, 2020).

The green cluster focuses on "unsupervised learning" and related topics such as "graph embeddings" and "node classification". The topics in this cluster are related to unsupervised learning methods, which are useful for finding patterns in data without the need for labels. Additionally, graph-based approaches are often used to analyze relationships between entities in complex networks, such as social networks, biological data analysis, and graph representation (Z. Wu, 2021). The relationship between these topics shows a focus on developing more efficient methods for handling large-scale and high-complexity data. The blue cluster includes topics such as "data augmentation," "image enhancement," and "semantic segmentation." These topics focus on the preparation and processing of visual data to improve the quality of inputs in deep learning model training. Data augmentation is used to expand the dataset by creating variations of existing data, while image enhancement improves image quality for more accurate analysis (Shorten, 2019).

The chocolate cluster covers topics such as "drug discovery" and "bioinformatics", demonstrating the application of deep learning in biological and pharmaceutical sciences. In this cluster, deep learning technology is applied to discover new drugs, analyze genomic data, and understand complex relationships in biological data (J. Lee, 2020). This topic reflects the profound influence of deep learning on health and pharmaceutical research, especially in accelerating the drug discovery process by processing large amounts of biological data. The orange cluster focuses on topics such as "federated learning" and "edge computing". Federated learning is a machine learning approach that allows models to be trained on data spread across multiple devices without moving the data to a central server, maintaining data privacy. Meanwhile, edge computing deals with processing data near its source to improve efficiency (L. Wang, 2020).

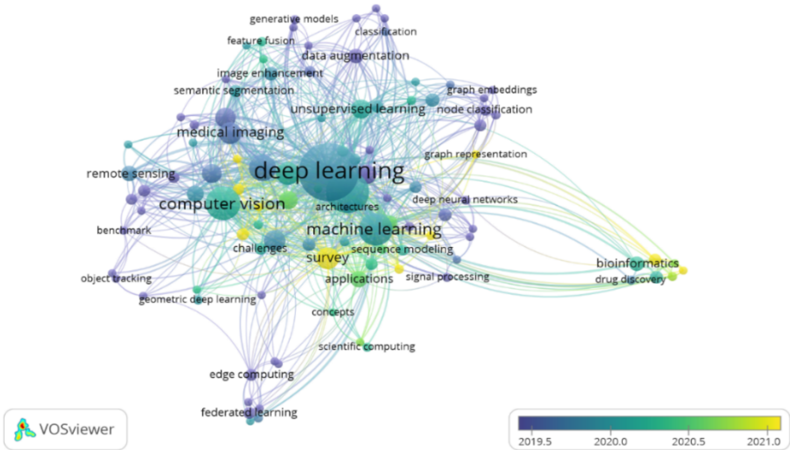

Figure 4. Temporal Network Visualization of Deep Learning Research Themes (2019–2024)

This visualization highlights how deep learning is at the core of many modern researches, with a wide range of linkages to various subfields and applications. The dominance of topics such as "computer vision" and "medical imaging" underscores the important role of deep learning in visual data processing. Meanwhile, diversification into topics such as "unsupervised learning" and "drug discovery" shows the flexibility of these technologies to be applied in a variety of contexts. This map also shows the importance of inter-disciplinary collaboration in research. With the continued development of deep learning technology, this map is a valuable guide to understanding key trends and focuses in the scientific community (Kaplan, 2020).

c. Keyword Correlation Analysis Based on Overlays in Network Visualization

The figure 4 displayed visualization is a bibliometric map of the relationships between topics in research created using VOSviewer software. This graph shows the connections between various keywords in the fields of deep learning and machine learning, with temporal analysis illustrated through color gradation. The size of each node (point) reflects how often the term appears in academic publications, where keywords such as deep learning, computer vision, and machine learning have larger sizes, indicating their dominance in research. The relationships between nodes are represented by edges, which show the connections between keywords based on their co-occurrence in the scientific literature. The thicker the connecting line, the closer the relationship between the two terms in the research (Mehrabi, 2022).

In addition, this visualization uses a color scheme to show time trends based on the publication period of the research. The blue color indicates keywords that appeared more frequently in publications before 2020, while the yellow color indicates keywords that were more dominant in recent research up to 2021. From this visualization, we can see that topics such as deep learning, computer vision, and medical imaging have been strong in previous research, while fields such as bioinformatics and drug discovery have appeared more in recent research. This indicates a shift in focus from deep learning applications in image processing to its application in the biomedical field (Vamathevan, 2019).

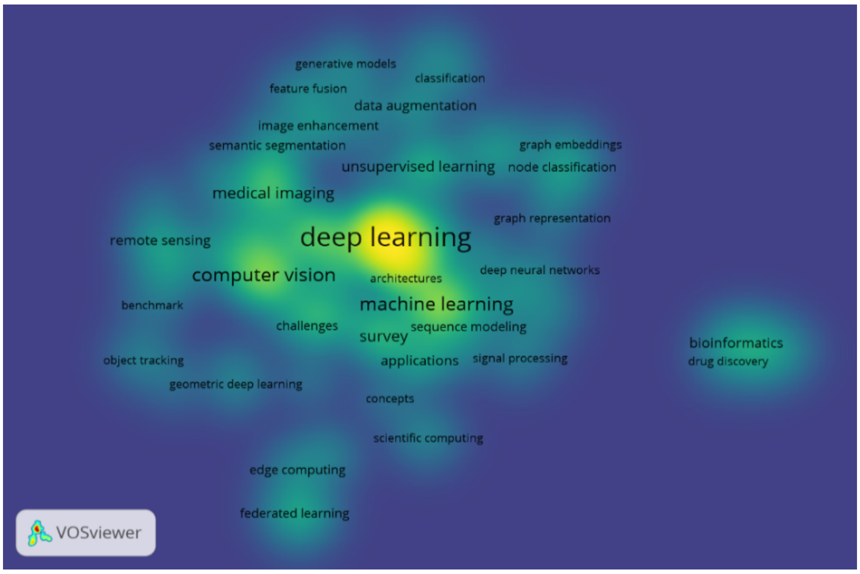

Figure 5. Heatmap of Research Focus in Deep Learning and Related Themes

Furthermore, the relationships between topics demonstrate how deep learning is applied across various fields. Computer vision is closely linked to medical imaging, remote sensing, semantic segmentation, and object tracking, indicating that this method is frequently utilized in the medical field and geospatial mapping. Conversely, terms like bioinformatics and drug discovery are increasingly associated with deep learning, indicating a rise in the application of artificial intelligence in pharmaceutical and medical research. Additionally, the emergence of new topics such as graph embeddings, federated learning, and edge computing reflects advancements in more distributed and efficient computing techniques (Sebastian, 2020).

Overall, this bibliometric map provides in-depth insights into how research in the field of deep learning and machine learning has evolved from 2019 to 2021. Although computer vision and medical imaging are still dominant topics, research is starting to shift to the biomedical field, as seen from the increasing number of studies in bioinformatics and drug discovery (Xiong, 2021). In addition, the emergence of new techniques such as federated learning and edge computing shows the exploration of more secure and decentralized computing methods. This trend indicates that the future of deep learning will increasingly focus on privacy, efficiency, and cross-disciplinary adoption. By understanding these patterns, researchers can identify recent research trends and development opportunities in the field of artificial intelligence (Sattler, 2020).

d. Keyword Relevance Analysis Based on Density in Network Visualization

This visualization on figure 5 is a density visualization generated using VOSviewer software. This graph shows the intensity of the linkage and popularity of various topics in deep learning-related research. The map uses a color scheme to depict the density level of a keyword or topic, where light colors (yellow) indicate a high frequency of occurrence and greater density, while dark colors (blue to purple) indicate a lower frequency of occurrence.

The displayed visualization is a keyword density map generated using VOSviewer software, which is commonly used in bibliometric analysis to map the relationships between concepts in academic literature. This map illustrates the density of keywords that frequently appear in deep learning research, where lighter colors (yellow) indicate keywords that appear more often and are more influential in the academic community, while green to blue colors signify terms with a lower frequency of occurrence. Therefore, this visualization provides an overview of the distribution and interconnection of various concepts in deep learning research, as well as assists in identifying the most rapidly developing research areas (Qin, 2019).

From this map, it can be observed that "Deep Learning" is the keyword with the highest density, indicated by a bright yellow color in the center of the visualization. This indicates that Deep Learning is a major topic in the mapped research, with various sub-fields and applications related to it. Some of the terms that are closely related to Deep Learning include "Computer Vision", which refers to the application of Deep Learning in image and video analysis, and "Machine Learning", which shows that Deep Learning is part of a broader approach to machine learning. In addition, "Medical Imaging" has also emerged as one of the high-density topics, signaling that Deep Learning is widely used in medical imaging analysis and other healthcare applications (Siddique, 2021).

The relationship between concepts in this map can also be seen from the distribution of keywords that are close to each other. For example, "Deep Learning" has a strong connection with "Unsupervised Learning", which suggests that research in this area also focuses heavily on labelless learning methods. In addition, there is a close relationship between "Sequence Modeling" and "Signal Processing", which shows that Deep Learning is widely used in sequential data analysis, such as natural language processing (NLP) and voice signal processing. Furthermore, concepts such as "Graph Embeddings" and "Node Classification" that appear on the outside of the map show that Deep Learning research is beginning to be widely applied in network-based and graph-based analysis (Veličković, 2019).

In addition to the main topics that dominate, there are also several research fields that are still developing and have the potential to become new trends in the next few years. For example, "Federated Learning" and "Edge Computing" show increased interest in optimizing distributed learning models and AI processing efficiency in resource-constrained devices (Sebastian, 2020). Meanwhile, "Bioinformatics" and "Drug Discovery" appear to be located in a more separate part of the core of the map, indicating that although it is still in its early stages, the application of Deep Learning in biology and pharmacy is beginning to receive more attention in the academic community. Therefore, this keyword density map not only reflects current research trends but also provides insights into the potential development of Deep Learning technology in the future (Tan, 2019).

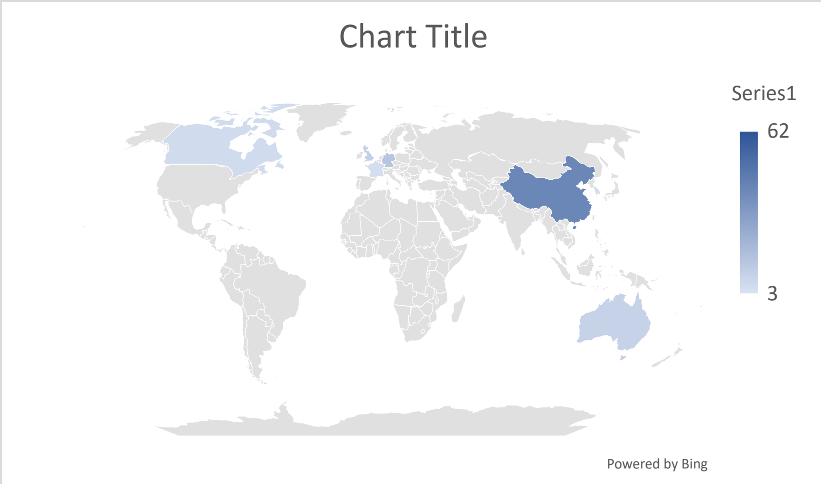

Figure 6. Global Distribution of Research Contributions by Country

e. Deep Learning Research Trends by Country

The world map in this visualization uses color gradations to represent the distribution of certain values based on geographic regions. The color intensity provides information about the difference in data levels, where the dark blue color indicates the highest value, light blue for the intermediate value, and gray for the lowest value or region that has no recorded data. The legend on the right side of the map explains the range of values from 3 to 62, which helps in understanding the distribution.

From the map, the United States leads in the distribution of Deep Learning data because it has many leading research centers, universities with advanced artificial intelligence (AI) programs, as well as large technology companies such as Google, Microsoft, and OpenAI. Many of the latest innovations in Deep Learning have come from these institutions, including advanced language models, deep learning algorithms, and AI applications applied in various sectors. This dominance is also reinforced by the availability of enormous computing resources and significant investments in the field of artificial intelligence (Zhou, 2020).

China, despite having a lower score than the United States, remains one of the key leaders in Deep Learning. The country has large companies such as Baidu, Alibaba, and Tencent that invest heavily in AI and deep learning. In addition, the Chinese government has also set a national strategy to become a global leader in artificial intelligence by 2030. With strong support from the government and rapid progress in research, China continues to catch up with the United States in this technology (Fuller, 2020).

In addition to the United States and China, several other countries such as Canada and Australia also have contributions in Deep Learning, albeit on a smaller scale. Canada, for example, has many well-known AI researchers, including Geoffrey Hinton who is known as one of the fathers of Deep Learning. Meanwhile, Australia continues to develop research in AI through universities and technology institutions. This map as a whole provides an overview of the development of Deep Learning is greatly influenced by countries that have strong resources, infrastructure, and policy support (Nishio, 2019).

Overall, this visualization confirms that developed countries are still major players in global scientific publications, with the US and China leading the way. However, other countries

Table 1. Distribution of the Number of Deep Learning Research Articles by Country

N0	Negara	Artikel
1	AS	62
2	China	41
3	Germany	15
4	UK	11
5	Australia	10
6	Singapura	7
7	Kanada	6
8	Korea Selatan	5
9	Prancis	5
10	Hong kong	3

in Europe and Asia are also increasingly strengthening their presence in the world of research. This shows that investment in education, research infrastructure, and international collaboration contributes to a higher number of publications, as well as accelerating the development of science at the global level (Bergmann, 2019).

f. Global Contribution to Deep Learning research by country

Based on the table, here is the distribution of the number of research articles on deep learning by country. The United States (US) takes first place with 62 articles, making it the country with the largest contribution on this list. China follows in second place with 41 articles, indicating that the country also has an important role in academic publications. Germany is ranked third with 15 articles, followed by the United Kingdom (UK) with 11 articles, and Australia in fifth place with 10 articles. These countries generally have world-renowned universities and research centers (Hannun, 2019).

In addition to the top five countries, there are also other countries that contribute a smaller but still significant number of articles. Singapore recorded 7 articles, Canada had 6 articles, while South Korea and France contributed 5 articles each. Hong Kong ranks tenth with 3 articles, making it the country with the fewest number of articles on this list.

From this table, it can be concluded that countries with strong economies and advanced education systems tend to dominate the number of academic publications. The United States and China, as the world's two largest economic powers, have high levels of research production. In addition, European countries such as Germany, the United Kingdom, and France also play an important role in academia, while Asian countries such as Singapore, South Korea, and Hong Kong also contribute to a smaller amount.

g. Minor Contributions and Local Perspectives in Deep Learning research

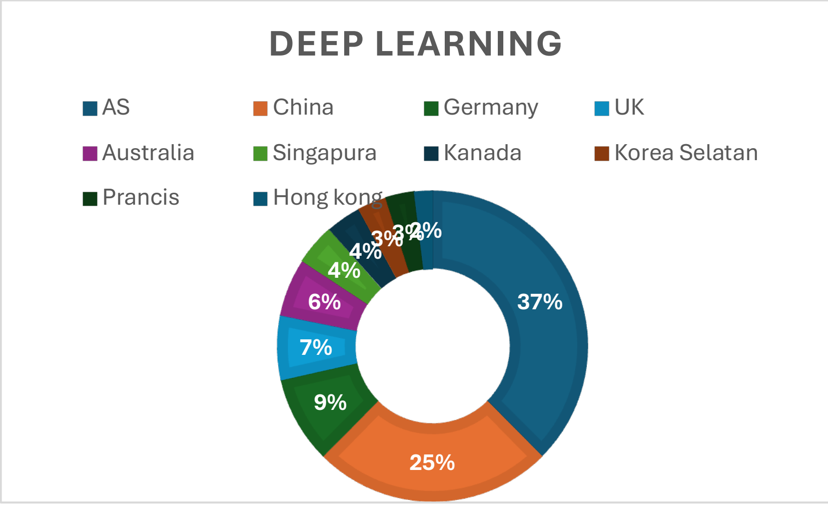

Figure 7. Distribution of the Number of Deep Learning Research Articles by Country

The donut diagram displayed is a representation of research contributions in the field of Deep Learning from various countries based on the percentage of publications. This diagram provides a visual representation of the dominance of certain countries in the development of artificial intelligence (AI) technology, especially in the sub-field of Deep Learning. Each country is represented by a different color to facilitate the identification of its relative contribution to the total research.

The United States holds the largest portion of Deep Learning research with 37% of total publications. This shows that the US is a major leader in AI research and development. Leading universities such as MIT, Stanford, and UC Berkeley as well as major tech companies such as Google, Microsoft, and OpenAI have played a major role in the advancement of Deep Learning. U.S. dominance is also supported by large investments in AI research, the availability of high computing infrastructure, and close collaboration between academia and industry (Arrieta, 2020).

China is in second place with a contribution of 25%. The rapid growth in the field of AI in China is strongly supported by government policies, which encourage innovation and research of advanced technologies. Companies such as Baidu, Alibaba, and Tencent, along with academic institutions such as Tsinghua University and the Chinese Academy of Sciences, play a major role in developing Deep Learning techniques. China also has many large-scale datasets used to train advanced AI models, making it a strong competitor to the U.S. in AI technology innovation.

With a contribution of 9%, Germany is a European country with a significant role in Deep Learning research. Research centers such as the Max Planck Institute, the Fraunhofer Institute, and the Technical University of Munich (TUM) conduct many studies in the field of AI and deep learning. In addition, Germany also has technology companies involved in AI research, especially in industrial and automotive applications such as image recognition systems for autonomous vehicles (Pouyanfar, 2019).

The UK contributes 7%, making it one of the countries with strong AI research in Europe. Universities such as Oxford, Cambridge, and Imperial College London are major AI research centers that often produce breakthroughs in the field of Deep Learning. In addition, the presence of companies such as DeepMind, which is based in London and is part of Google, makes the UK one of the leaders in global AI innovation (Khan, 2020).

Australia accounts for 6% of the total publications, which shows that the country has a fairly active AI research community. Universities such as the University of Melbourne and the Australian National University are involved in a wide range of research related to Deep Learning. The Australian government has also increased investment in AI to strengthen the country's position in the digital economy and technology (Q. Wang, 2020). As a small country with a technology-based economy, Singapore still has a significant contribution to AI research with 4%. The National University of Singapore (NUS) and Nanyang Technological University (NTU) play a leading role in AI research in Southeast Asia. Singapore also has various AI research centers and startups that focus on the development of Deep Learning-based technologies. Canada has a contribution of 4%, which is driven by a strong research ecosystem. Toronto and Montreal are major AI research hubs in Canada, with the University of Toronto and the University of Montreal having some of the leading AI experts such as Geoffrey Hinton and Yoshua Bengio. The country is also home to many AI labs from global companies such as Google and Facebook (Floridi, 2020).

South Korea accounts for 3% of total Deep Learning research. The country has big tech companies such as Samsung and LG that are active in AI development. In addition, universities such as Seoul National University and KAIST often conduct research in the field of AI and deep learning. France contributes 3%, with several major AI research centers such as INRIA and the University of Paris-Saclay focusing on the development of Deep Learning algorithms and applications. The country also has government programs that support AI research and development (K. Lee, 2019). Despite its small size, Hong Kong accounts for 3% of total Deep Learning publications. The City University of Hong Kong and the Hong Kong University of Science and Technology are two leading institutions that are driving AI research in the region. Hong Kong also has a variety of tech startups that focus on Deep Learning-based innovation (Istenič, 2021).

h. Deep Learning Research Trends Based on Affiliation

The horizontal bar chart on figure 8 displayed provides an overview of the top 10 institutions based on the total contribution of citations in Deep Learning research. This graph shows the extent to which each institution contributes to research and publications in this area, with the length of the bar representing the total number of citations received by publications from each institution. Citations are an important metric in academic research, as they show the extent to which a study is used and recognized by the scientific community. The higher the number of citations an institution has, the greater its impact on the Deep Learning research community.

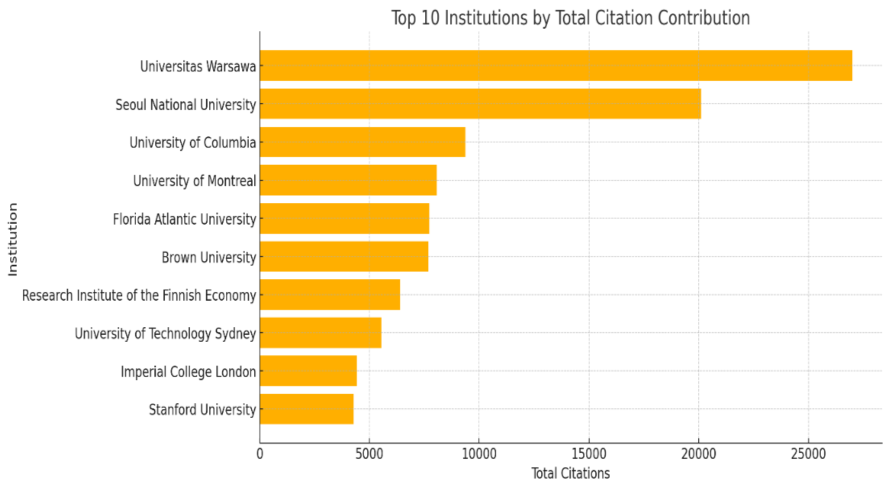

Figure 8. Top 10 Institutions with the Most Contributions in Deep Learning Research

The institution with the highest number of citations is the University of Warsaw, which recorded more than 25,000 citations. This shows that these universities have a huge impact in Deep Learning research, both in the number of publications and in the quality of the research they produce. The second position is occupied by Seoul National University, which also has a high number of citations, approaching 20,000 citations. This confirms that South Korea is one of the countries with a major contribution to the development of artificial intelligence (AI), supported by government policies and technology companies such as Samsung and LG. The academic contributions of these two institutions show that they play a major role in the development of AI-based technologies in their respective regions (Mehrabi, 2022).

In third place, the University of Columbia shows a significant number of citations. Columbia is known as one of the world's leading AI research centers, with various collaborations with major tech industries. The University of Montreal is in fourth place, which is not surprising given that Canada is a very powerful center for AI research. One of the pioneers of Deep Learning, Yoshua Bengio, hails from this university, and the AI community in Canada is known to be very active in the development of deep learning models. The presence of the University of Montreal on this list shows that Canada has a competitive and innovative AI ecosystem, with many research laboratories producing breakthroughs in AI technology (Gou, 2021).

In the next ranking, Florida Atlantic University and Brown University have a high number of citations, which indicates that they contribute significantly to AI research despite not being institutions that are generally considered leaders in AI. The Research Institute of the Finnish Economy is also included in this list, showing that in addition to universities, independent research institutions also play an important role in the development of AI. The University of Technology Sydney, which hails from Australia, has also shown considerable contribution to AI research. This indicates that AI research is not only dominated by universities in the United States or Europe, but also develops in various other parts of the world (Tan, 2019).

The last two institutions on this list are Imperial College London and Stanford University. Imperial College London, based in the UK, has one of the best AI research programs in Europe, while Stanford University is an institution known as a leader in AI technology and is often the birthplace of the latest technological innovations. Despite being ranked last on this list, Stanford still has a great influence on AI research globally. Many of the latest technologies in machine learning and Deep Learning come from research conducted by academics at Stanford, which shows the importance of this institution in the advancement of AI (Abramson, 2024).

Overall, this diagram shows that Deep Learning research is widespread in different countries, with dominance from institutions in North America, Europe, and Asia. The University of Warsaw and Seoul National University dominate with the highest number of citations, demonstrating the enormous academic impact of their research. With the growing development of artificial intelligence, it is predictable that more institutions will continue to increase their contribution to Deep Learning research, both through new publications and collaborations with the technology industry (Alzubaidi, 2021). This graph also shows that the field of AI continues to experience rapid growth, and more universities and research institutes are competing to make a significant contribution to the development of this technology.

4. Discussion

The bibliometric analysis of Deep Learning (DL) research from 2019 to 2024 reveals a convergence of computational efficiency, probabilistic modeling, and domain-specific applications such as computer vision, medical imaging, and natural language processing, reflecting the growing reliance of modern science on data-driven reasoning and multilevel statistical inference. These trends carry direct implications for the teaching of statistical mathematics, indicating that future curricula should emphasize spatial data analysis, multivariate modeling, and visualization techniques as foundational tools for interpreting high-dimensional data, while also integrating resampling methods such as bootstrapping, Monte Carlo simulation, and cross-validation early in the learning process to develop students' understanding of model generalization and uncertainty estimation. The observed network patterns connecting optimization, probability, and neural computation underscore the necessity of explicitly integrating mathematics, statistics, and computational science within instructional design, since teaching statistical mathematics in isolation limits learners' ability to apply theoretical constructs such as gradient descent, Bayesian updating, and stochastic processes to real-world problems. Deep Learning thus serves as a pedagogical bridge that concretizes abstract statistical ideas through its reliance on probabilistic reasoning, optimization, and iterative model training, demonstrating how statistical principles operate dynamically within complex data systems. Consequently, reforming statistics education in the digital era requires a paradigm shift from formulaic computation toward modeling- and interpretation-oriented pedagogy that values conceptual understanding, data literacy, and computational experimentation equally. Ultimately, the bibliometric trends in DL research not only mirror the evolution of global scientific.

The trend of citations and fluctuating publication patterns from year to year, as illustrated in the research results, also provides an interesting insight into the dynamics of knowledge development. In the context of learning statistics, this data can be used as a means of evidence-based learning that emphasizes the importance of data-driven thinking (Deswita & Ningsih, 2025). Learners can be invited to analyze publication trend graphs using both descriptive and inferential statistical tools. From these activities, they not only practice skills such as calculating averages, deviations, or correlations, but also learn to interpret data logically and argumentatively. This process shifts the paradigm of statistics learning from merely performing calculations to engaging in reflective thinking that requires the ability to understand the meaning behind the numbers.

Furthermore, the visualization of topic networks and density maps in this study provides a tangible illustration of how relationships between variables can be represented visually. This aligns with the essence of learning statistical mathematics, which aims to instill an understanding of the interconnections among elements within a dataset (Mulianah et al., 2025). Through thematic maps such as network visualization or density maps, students can grasp concepts like multivariate statistics, cluster analysis, and correlation mapping in a more concrete context. By observing how topics such as computer vision or medical imaging are thematically related to deep learning, students can be trained to read complex data structures systematically. This approach makes statistics not just a collection of formulas, but a way of thinking that emphasizes order, interconnectedness, and patterns.

The differences in contributions between countries, as revealed through the distribution of publications, also add a social and global dimension to learning statistical mathematics. Such data can be used to train students in performing comparative data analysis, such as comparing the number of publications between countries, calculating ratios, or identifying the relationship between socio-economic variables and scientific productivity. From this, learners are invited to understand that statistics has interpretive power over social phenomena, that numbers do not stand alone, but represent the social, economic, and public policy dynamics that influence the development of science. Thus, learning statistical mathematics not only hones numerical skills but also fosters sensitivity to the social meaning of the data being analyzed.

Findings on the emergence of new fields such as federated learning and edge computing indicate that statistics continue to evolve alongside technological developments. In the context of education, this underscores the need to update curricula so that statistical materials remain relevant to the needs of modern data analysis. Topics such as sampling theory, probability distributions, and statistical inference can be linked to concepts of distributed data analysis or decentralized computing, where data is collected from various sources without losing analytical consistency. By understanding these concepts, students not only master classical theory but also recognize contemporary issues such as data privacy, computational efficiency, and information security. This represents a new direction in statistics education that demands both technical mastery and ethical awareness.

From a pedagogical perspective, the results of this study emphasize the importance of a project-based learning approach in statistics mathematics education. Through data-based projects, students can directly learn how to collect, process, and interpret real-world data, for example by analyzing publication trends or global research networks as done in Deep Learning research. This approach makes learning more contextual and meaningful because students are not only dealing with numbers on paper but with data that reflects scientific reality. In addition, this method also develops 21st-century skills such as critical thinking, collaboration, and scientific communication skills, which are highly needed in the data- and research-based workforce.

Ultimately, this study shows that the learning of statistical mathematics needs to move towards an integrative and interdisciplinary approach. Deep Learning serves as a concrete example that advances in modern technology are deeply rooted in the principles of statistics, probability, and mathematical optimization. Therefore, students need to be encouraged to understand that concepts such as probability distributions, Bayesian inference, and regression are not merely theoretical, but the foundation of the technologies that shape the future. Through teaching that connects statistical theory with its application in technological contexts such as artificial intelligence, learning becomes more vivid and relevant. Thus, education in statistical mathematics not only equips students with computational skills but also with the ability to understand the world through the lens of data and critical scientific analysis.

This study carries important implications that learning statistical mathematics should be directed toward developing analytical and interpretative thinking skills based on real data. Teachers or lecturers should not only emphasize mathematical calculations but also the understanding of the meaning behind the data. Trend analysis, topic networks, and research distributions as found in this study can serve as practical examples of how statistical concepts are used to identify patterns, relationships, and changes in scientific phenomena. By utilizing data visualization and analytical tools such as R, Python, or Excel, students will become accustomed to seeing statistics as a tool for scientific thinking that helps explain reality, not just a collection of formulas.

In addition, the teaching of statistical mathematics in the digital era should not eliminate computational practice but rather transform its nature from manual calculation to programming-based computation and model-driven reasoning. Deep Learning itself exemplifies how mathematical and statistical principles operate through intensive numerical processing, matrix algebra, and algorithmic iteration. Therefore, statistics education should integrate project-based and computational learning approaches that enable students to translate theoretical formulas into executable algorithms. By engaging with real world data such as global Deep Learning research trends students not only strengthen their ability to process large and complex datasets but also develop a deeper understanding of how statistical models function within computational environments. This paradigm encourages learners to use coding and visualization tools (e.g., Python, R, or MATLAB) to explore concepts such as regression, probability, and optimization dynamically rather than statically. In doing so, students cultivate not only numerical fluency but also data literacy, ethical awareness, and interdisciplinary insight that connect statistics with computer science and applied problem solving. Consequently, the teaching of statistical mathematics becomes both conceptually rich and computationally relevant, preparing learners to navigate the data-driven challenges of the artificial intelligence era where analytical reasoning and algorithmic computation are inseparable.

5. Conclusion

The development of Deep Learning research in the 2019–2024 period shows rapid, multidimensional dynamics increasingly rooted in the integration of statistical mathematics and artificial intelligence. Bibliometric analysis results indicate that Deep Learning has reached a maturity phase, with a shift in focus from the development of basic models to interdisciplinary applications such as biomedicine, pharmaceuticals, and distributed computing. The peak of scientific activity occurred in 2022 before stabilizing, while topic network visualization highlights the dominance of the fields of "computer vision" and "medical imaging," as well as the emergence of new trends such as "federated learning" and "edge computing," which mark the direction of innovation towards data privacy and computational efficiency. Geographically, the United States and China lead in global contributions, followed by Germany, the United

Kingdom, and Australia, which show strong research collaboration. Conceptually, this study emphasizes that learning statistical mathematics in the digital era needs to transform from a mechanistic approach to an interpretative and applicative approach, where statistics functions as a scientific language for understanding large and complex data. The integration of data-driven analysis, scientific visualization, and project-based learning becomes key in shaping a critical, adaptive scientific mindset that is relevant to the needs of the artificial intelligence era and multidisciplinary collaboration.

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