Exploring the Impact of Deep Learning in Acute Lymphoblastic Leukemia Diagnosis: A Bibliometric Perspective

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Abstract

Acute Lymphoblastic Leukemia (ALL) is a serious hematologic malignancy that requires prompt and accurate diagnosis for effective treatment. Traditional diagnostic approaches, such as microscopic inspection and flow cytometry, while reliable, are labor-intensive and time-consuming. Deep learning (DL), particularly Convolutional Neural Networks (CNNs), has revolutionized ALL diagnosis by automatically extracting features from medical images with an accuracy comparable to experienced hematologists. This automation enhances diagnostic precision and significantly reduces diagnosis time, ultimately improving clinical decision-making and patient outcomes. This study uses deep learning through rigorous bibliometric analysis to examine research productivity indicators related to the classification of Acute Lymphoblastic Leukemia. The dataset comprises 152 publications on ALL classifications using deep learning from 2009 to 2023. The analysis is conducted using the R Bibliometrix library. These publications, authored by 654 researchers from 38 countries, are distributed across 99 sources, including journals and books. Collectively, the corpus has received 1,770 citations, with an average of 11.8 citations per document. The most-cited paper, Leukemia Diagnosis in Blood Slides Using Transfer Learning in CNNs and SVM for Classification by Luis H.S. Vogado et al., has been cited 143 times. In terms of global scientific output, India leads with 26 publications (17.3%), followed by China with 22 (14.7%) and the United States with 16 (10.7%).

Keywords: bibliometric analysis; R Bibliometrix; Acute Lymphoblastic Leukemia; Deep Learning; Web of Science.

المستخلص

تعد اللوكيميا الليمفاوية الحادة (ALL) من الأمراض الخبيثة الدموية الخطيرة التي تتطلب تشخيصًا سريعًا ودقيقًا للعلاج الفعال. تعتبر الطرق التقليدية مثل الفحص المجهري وتدفق الخلايا دقيقة وموثوقة لكنها تتسم بالعمل المكثف واستغراق الوقت. أحدث التعلم العميق(DL) ، وخاصة الشبكات العصبية التلافيفية(CNNs) ، تحولاً في تشخيص اللوكيميا الليمفاوية الحادة من خلال استخراج الميزات تلقائيًا من الصور الطبية بدقة تضاهي دقة أطباء الدم ذوي الخبرة. لا تعزز هذه الأتمتة دقة التشخيص فحسب، بل توفر أيضًا وقتًا كبيرًا مما يحسن اتخاذ القرارات السريرية ونتائج المرضى. يهدف هذا العمل إلى دراسة مؤشرات الإنتاج البحثي المتعلقة بتصنيف اللوكيميا الليمفاوية الحادة باستخدام التعلم العميق من خلال تحليل ببليومتري دقيق. يتضمن التحليل 152 منشورًا عن تصنيف اللوكيميا الليمفاوية الحادة باستخدام التعلم العميق في الفترة بين 2009 و2023. تم استخدام مكتبة R Bibliometrixلتحليل البيانات. كتب هذه الأعمال 654 مؤلفًا من 38 دولة، ونُشرت في 99 مصدرًا مختلفًا، بما في ذلك المجلات والكتب. حصل هذا الإنتاج العلمي على إجمالي 1770 استشهادًا، بمتوسط 11.8 استشهاد لكل وثيقة. حصلت الورقة البحثية الأعلى تصنيفًا، "تشخيص اللوكيميا في شرائح الدم باستخدام التعلم بالنقل في الشبكات العصبية التلافيفية ودعم آلات المتجهات للتصنيف" للمؤلف لويس إتش. إس. فوجادو وآخرين، على 143 استشهادًا. فيما يتعلق بالإنتاج العلمي العالمي، تصدرت الهند القائمة بـ 26 منشورًا (17.3%)، تليها الصين بـ 22 منشورًا (14.7%)، ثم الولايات المتحدة بـ 16 منشورًا.(10.7%)

1. INTRODUCTION

Leukemia, affecting over a million in the U.S., is a blood cancer caused by genetic abnormalities disrupting cell cycle regulation [1]. It differs from other cancers, affecting all ages [2]. Acute leukemia is fast and aggressive; chronic leukemia progresses slowly. The four primary types based on cellular origins are AML, CML, ALL, and CLL [3, 4, 5]. Early diagnosis and treatment are crucial, but manual detection is time-consuming [3]. AI, specifically machine learning and deep learning, shows promise in improving accuracy and efficiency in hematological disorder detection, especially in acute leukemia. These technologies analyze large datasets, such as blood cell images, to identify abnormalities and classify disorders [5]. Deep learning recognizes complex patterns in utilizing neural networks, making it suitable for image analysis in medical diagnosis, including leukemia detection [3, 6]. In parallel, bibliometric analysis, as asserted, is a rigorous statistical method providing a structured evaluation and analysis of scholarly publications and scientific output [7, 8]. This method seeks insightful perspectives on specific research fields' structure, impact, and trends. Bibliometric analysis unveils a field's cognitive structure and evolution, identifying trends and key research domains through meticulous detailing, evaluation, and tracking of published research. This analytical approach offers researchers a robust foundation to contextualize current contributions, discern noteworthy developments, and identify emerging directions for future research [9]. Applied across various fields, including operations research and management science [10], digital marketing [11], business process management [12], and artificial intelligence and machine learning, bibliometric analysis serves as a valuable tool for comprehending scientific production. Despite the burgeoning research publications on the Classification of Acute Lymphoblastic Leukemia Deep learning, a conspicuous absence of comprehensive reviews focused explicitly on the in-depth analysis of scientific output in this domain exists. This article endeavors to bridge this gap by employing bibliometric analysis, with the primary goal of dissecting the scientific landscape surrounding the Classification of Acute Lymphoblastic Leukemia Based Deep learning. The significance of this study lies in its potential to provide researchers with valuable insights into the current state and future research directions [13].

Section 1 serves as an introduction to the topic, while Section 2 delves into the problem formulation. Section 3 explores related work, Section 4 outlines the data and methods employed, Section 5 presents the results, and Sections 6 and 7 sequentially provide the discussion and conclude the study.

1.1 Problem statement

The detection and classification of Acute Lymphoblastic Leukemia (ALL) using deep learning (DL) face significant challenges. These include limited access to high-quality labeled datasets, imaging technique variability, and model interpretability issues. Additional obstacles involve ensuring that DL models generalize across institutions, addressing logistical and ethical concerns, and meeting the high computational demands that hinder widespread adoption. Tackling these challenges is essential for advancing DL-based diagnosis of ALL in clinical practice.

1.2 Aims

- This study aims to conduct a comprehensive bibliometric analysis of research on deep learning-based classification of Acute Lymphoblastic Leukemia (ALL) to evaluate trends, research productivity, and scientific impact. The key objectives include:
- Assessing Research Productivity: Analyzing the volume, growth, and geographical distribution of publications related to DL-based ALL classification.
- Identifying Key Contributors: Evaluating influential authors, institutions, and countries driving advancements in this field.
- Mapping Research Trends: Highlighting dominant themes, methodologies, and technological advancements in deep learning applications for ALL diagnoses.
- Evaluating Citation Impact: Measuring the influence of key publications and identifying highly cited works that have shaped the domain.
- Understanding Challenges and Future Directions: Identifying gaps in current research, including dataset limitations, model interpretability, and clinical integration, to guide future advancements.

1.3 Contributions

- This study contributes to the field by providing a structured bibliometric assessment of DL-based ALL classification research, offering insights into its evolution and impact. Specifically, it:
- Presents a quantitative analysis of 152 publications from 2009 to 2023, including citation metrics, author networks, and country-wise research distribution.
- Identifies influential research works and trends that have significantly improved ALL classification using deep learning.
- Highlights leading institutions and collaboration networks, facilitating knowledge sharing and interdisciplinary partnerships.
- Discusses research gaps and future directions, including challenges related to dataset availability, model generalization, interpretability, and clinical adoption.
- Supports decision-making for researchers and policymakers by providing a data-driven overview of progress in this domain, guiding future studies and investments.

1.4 Structures of the study

The remainder of this article is organized as follows: Section 2 reviews related work. Section 3 outlines the research methodology, including data sources, search strategy, and data analysis techniques. Section 4 presents the results, followed by a detailed discussion. Finally, Section 5 provides conclusions and directions for future research.

2. RELATED WORK

This study conducted a comprehensive bibliometric analysis to map the research trends and influential publications in deep learning applied to leukemia detection and classification. The study highlighted the rapid publication growth over the past decade, identifying key journals, countries, and institutions leading the research. The authors used various bibliometric indicators, such as citation analysis and co-authorship networks, to uncover the collaboration patterns and the most cited works in the field. They found that the United States and China were the most prolific countries, contributing significantly to advancements in this domain [14]. Abadi et al. utilized bibliometric methods to examine the evolution of deep learning applications in hematopathology, focusing on leukemia. This study analyzed publication data from multiple scientific databases, identifying trends in research output, influential authors, and emerging topics. The analysis revealed a growing interest in integrating convolutional neural networks (CNNs) for automated classification of leukemic cells. The study also highlighted the challenges of data standardization and the need for more collaborative research efforts to enhance the robustness and generalizability of DL models [15]. Esteva et al. performed a bibliometric analysis to evaluate the impact of deep learning in medical computer vision, specifically in leukemia diagnosis. The study assessed the citation trajectories of key papers, collaboration networks, and the impact of conferences and journals in disseminating research findings. Esteva and colleagues found that interdisciplinary collaborations between computer scientists and medical professionals were crucial for successfully applying DL techniques in leukemia classification. Their analysis emphasized the importance of large, annotated datasets and the development of interpretable models to gain clinical acceptance [16].

Wei et al. presented a bibliometric review focusing on applying deep learning in the automatic analysis of leukemia. The study utilized bibliometric tools to analyze publication patterns, key research themes, and influential works. They found that using CNNs and transfer learning techniques was prevalent in recent studies. Wei et al. also identified a need for more research on explainable AI methods to address the black-box nature of deep learning models, which is critical for clinical adoption and trust [17].

Liu Y et al. present an automated deep-learning model explicitly designed for segmenting leukemic cells from blood smear images. The model incorporates an optimization mechanism to enhance the segmentation accuracy. The model can effectively distinguish between leukemic and non-leukemic cells by leveraging convolutional neural networks (CNNs) with advanced optimization techniques. The study demonstrates that the optimized deep-learning model significantly improves segmentation performance, making it a valuable tool for aiding hematologists in diagnosing leukemia from blood smear images [18].

Ahmed S et al. explore using hybrid and ensemble deep learning architectures to detect leukemia. The study aims to enhance diagnostic accuracy and robustness by combining multiple deep-learning models. The hybrid architecture integrates features from various models, while the ensemble approach averages the predictions from different models to achieve better performance. The results indicate that these advanced architectures outperform individual models, providing more reliable and accurate leukemia detection [19].

Kim J et al. focus on classifying peripheral blood smear images to diagnose Acute Lymphoblastic Leukemia (ALL) using an improved convolutional neural network (CNN). The improved CNN architecture incorporates advanced layers and optimization techniques to enhance feature extraction and classification accuracy. The research demonstrates that the improved CNN significantly outperforms traditional models, providing a reliable and efficient method for diagnosing ALL from peripheral blood smear images [20].

Zhang H et al. investigate the application of deep learning and explainable artificial intelligence (AI) for gene selection in predicting the need and timing of therapy for chronic lymphocytic leukemia (CLL). The study uses deep learning models to identify key genes associated with CLL progression and treatment requirements. The explainable AI component ensures that the model's decisions are transparent and interpretable, allowing clinicians to understand the rationale behind gene selection and predictions. This approach enhances the ability to tailor treatment plans for CLL patients based on genetic profiles [21].

3. Methodology

A systematic review following the PRISMA framework was conducted to analyze scientific publications on Acute Lymphoblastic Leukemia (ALL) classification using deep learning from the Web of Science database. The search, focusing on titles and author keywords, used terms like deep learning, leukemia, Convolutional Neural Networks (CNN), and Long Short-Term Memory (LSTM), yielding 152 publications (2009–2023).

After applying inclusion-exclusion criteria, relevant studies were selected for bibliometric analysis using the R Bibliometrix package[23]. The analysis covered publication trends, citation impact, key authors, institutional affiliations, journal sources, and keyword co-occurrence, providing insights into the research landscape on deep learning applications in ALL classification.

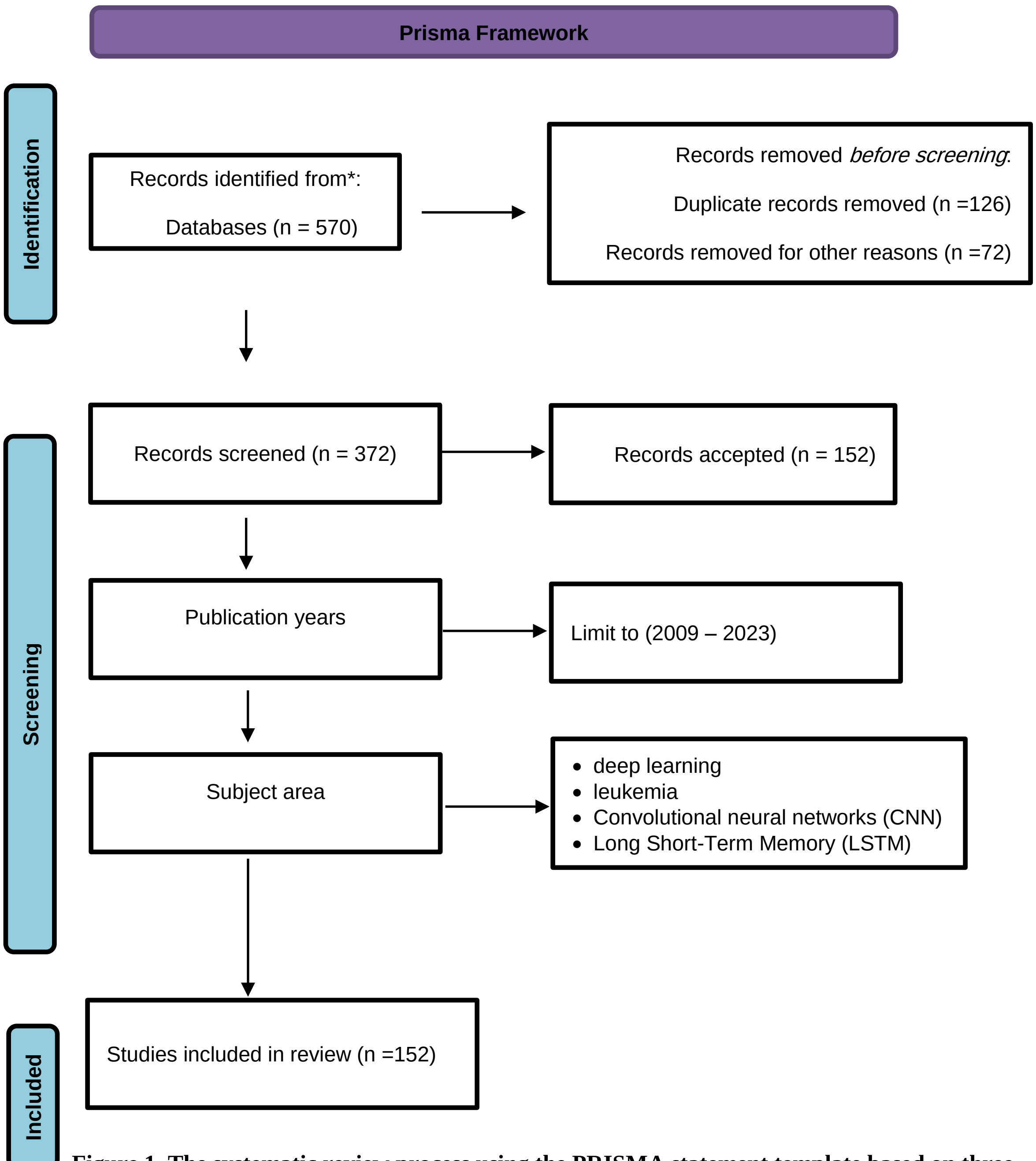

Figure 1. The systematic review process using the PRISMA statement template based on three phases that are identification, screening and included.

4. Results

The Web of Science database discovered 152 publications on the Classification of Acute Lymphoblastic Leukemia Deep learning published from 2009 to 2023. These publications were written by 654 authors from 38 countries and were published in 99 different forms (journals, books, etc.). Moreover, 1770 citations were made to the publications, averaging 11.80 per document.

The retrieved documents covered 9 document types, with 99 articles comprising 71.1% of the overall production and 148 (22.0%) proceedings papers. Other document types include reviews, book reviews, early access, book chapters, editorial materials, and letters, which were 46 (6.9%).

4.1 Trends analysis

Figure2. shows that there has been an increase in interest in the Classification of Acute Lymphoblastic Leukemia Deep learning research since 2009, with more than 10 documents published since 2019. However, it peaked in 2022 with 46 papers published compared to 20 documents in 2021, 18 in 2020, and 11 in 2019.

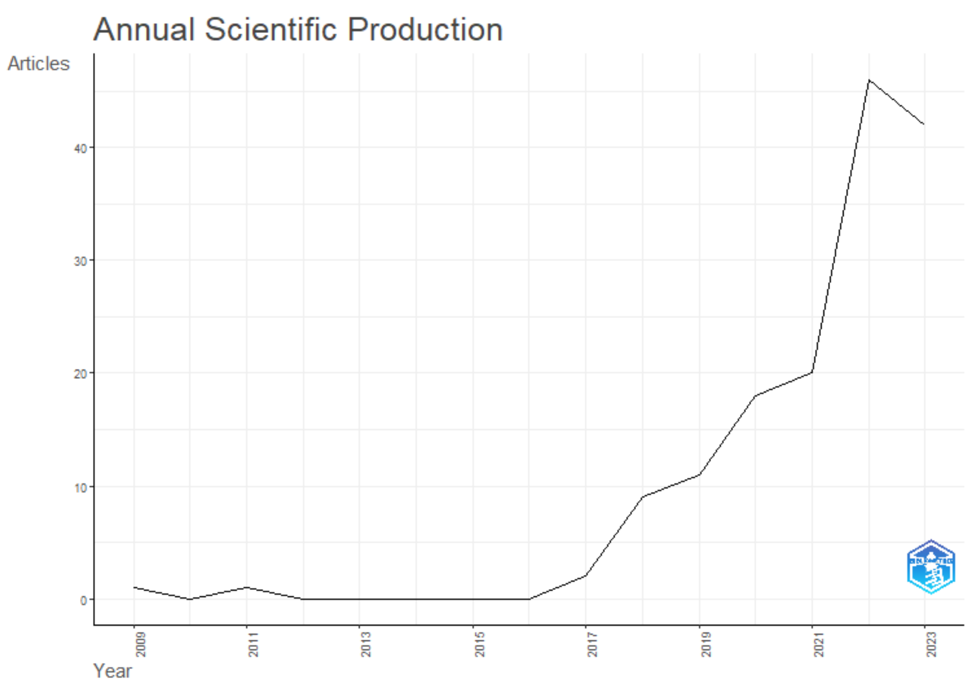

Figure 2. Annual trend per year of publications on Classification of Acute Lymphoblastic **Leukemia Based** Deep Learning.

4.2 Most cited and influential publications

Table 1. presents the 10 most cited publications in the Acute Lymphoblastic Leukemia Based Deep Learning Classification. The total number of citations (Global citations) varies from 40 to 143. With 143 citations, the top-ranked article is “Leukemia diagnosis in blood slides using transfer learning in CNNs and SVM for classification.” authored by VOGADO LHS.

Table 1. Top 10 cited articles.

Rank	Paper Title	Author	DOI	Total Citations
1	Leukemia diagnosis in blood slides using transfer learning in CNNs and SVM for classification.	VOGADO LHS	10.1016/j.engappai.2018.04.024	143
2	Classification of acute lymphoblastic leukemia using deep learning 1	REHMAN A	10.1002/jemt.23139	132
3	Acute Lymphoblastic Leukemia Detection and Classification of Its Subtypes Using Pretrained Deep Convolutional Neural Networks 2	SHAFIQUE S	10.1177/1533033818802789	113
4	Array-based genomic screening at diagnosis and during follow-up in chronic lymphocytic leukemia 3	GUNNARSSON R	10.3324/haematol.2010.039768	79
5	Identification of Leukemia Subtypes from Microscopic Images Using Convolutional Neural Network 4	AHMED N	10.3390/diagnostics9030104	62
6	Frequent genomic abnormalities in acute myeloid leukemia/myelodysplastic syndrome with normal karyotype **5**	AKAGI T	10.3324/haematol.13024	57
7	Mutual Information-based hybrid model and deep learning for Acute Lymphocytic Leukemia detection in single cell blood smear images 6	JHA KK	10.1016/j.cmpb.2019.104987	52
8	An efficient deep Convolutional Neural Network detection and classification of Acute Lymphoblastic Leukemia 7	DAS PK	10.1016/j.eswa.2021.115311	48
9	IoMT-Based Automated Detection and Classification of Leukemia Using Deep Learning 8	BIBI N	10.1155/2020/6648574	47
10	Deep Transfer Learning in Diagnosing Leukemia in Blood Cells 9	LOEY M	10.3390/computers9020029	40

4.3 Authorship analysis

The ten most prolific and influential authors in the Classification of Acute Lymphoblastic Leukemia Deep Learning are depicted in Figure 3. With five publications, Liu Y and Wang L are the most productive and influential scholars, followed by Das Pk and Genovese A with four publications each.

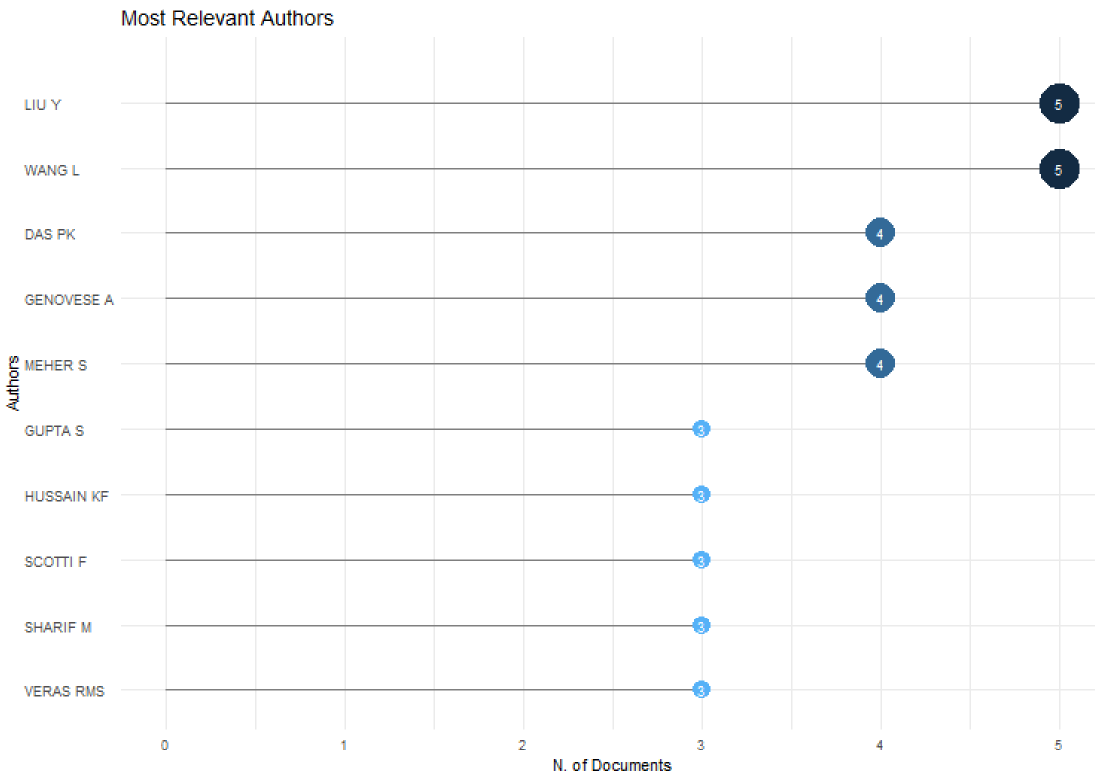

Figure 3. Top 10 Acute Lymphoblastic Leukemia Based Deep Learning Classification authors.

4.4 Co-authorship network analysis

Based on the data retrieved from the Web of Science, 1,689 distinct authors wrote the sampled publications. The analyses of co-authorship are displayed in Table 2.

Table 2. Co-authors' network analysis

From	To	Frequency
INDIA	SAUDI ARABIA	4
PAKISTAN	SAUDI ARABIA	4
INDIA	UNITED STATES	3
PAKISTAN	UNITED KINGDOM	3
BRAZIL	PORTUGAL	2
CHINA	GERMANY	2
CHINA	PAKISTAN	2
CHINA	SAUDI ARABIA	2
ITALY	CANADA	2
PAKISTAN	EGYPT	2
PAKISTAN	KOREA	2
SAUDI ARABIA	EGYPT	2
SAUDI ARABIA	MALAYSIA	2
SAUDI ARABIA	UNITED KINGDOM	2
UNITED STATES	GERMANY	2
UNITED STATES	SAUDI ARABIA	2
AUSTRIA	ARGENTINA	1
CHINA	NIGERIA	1
GERMANY	JAPAN	1
UNITED STATE	SPAIN	1

4.5 Most Productive Countries

Table 3. indicates that among the 32 countries that were productive in publications in the field of Classification of Acute Lymphoblastic Leukemia Deep learning, India is the leading country with 26 publications (17.3%), followed by China with 22 publications (14.7%) and the United States with 16 publications (10.7%).

Table 3. The ten most productive and cited countries.

Rank	Country	Number of Publications	Percentage	Total Citations	Average Article Citations	Single country publications (SCP)	Multiple country publications (MCP)	MCP Ratio
1	INDIA	26	17.3	300	11.5	23	3	0.11
2	CHINA	22	14.7	199	9	20	2	0.09
3	UNITED STATE	16	10.7	142	8.9	12	4	0.25
4	SAUDI ARABIA	10	7.0	186	18.6	4	6	0.6
5	ITALY	9	6.0	54	6	5	4	0.4
6	PAKISTAN	8	5.0	202	25.2	3	5	0.62
7	BRAZIL	6	4.0	197	32.8	4	2	0.33
8	EGYPT	6	4.0	41	6.8	6	0	0
9	KOREA	6	4.0	41	6.8	3	3	0.5
10	GERMANY	5	3.0	60	12	5	0	0

4.5 Sources and h-index analysis

Disseminating Knowledge: Mapping the publication of the landscape of Classification of Acute Lymphoblastic Leukemia Based Deep learning, this figure delves into the publication channels for research on the Classification of Acute Lymphoblastic Leukemia Deep learning, showcasing the 99 distinct journals that have published articles in this domain. Analyzing publication count and h-index values sheds light on the preferred outlets for disseminating research findings.

Table 4. Most Relevant Sources

Rank	Sources	Number of publications	H-index	Total citations	Year of start
1	DIAGNOSTICS	12	5	109	2019
2	IEEE ACCESS	8	4	74	2020
3	MULTIMEDIA TOOLS AND APPLICATIONS	7	2	6	2022
4	ISBI 2019 C-NMC CHALLENGE: CLASSIFICATION IN CANCER CELL IMAGING	5	4	55	2019
5	APPLIED SCIENCES-BASEL	4	4	52	2020
6	COMPUTERS IN BIOLOGY AND MEDICINE	3	3	24	2022
7	BIOMEDICAL SIGNAL PROCESSING AND CONTROL	3	2	44	2021
8	SENSORS	3	2	40	2022
9	BLOOD	3	1	4	2018
10	COMPUTATIONAL INTELLIGENCE AND NEUROSCIENCE	2	2	40	2021

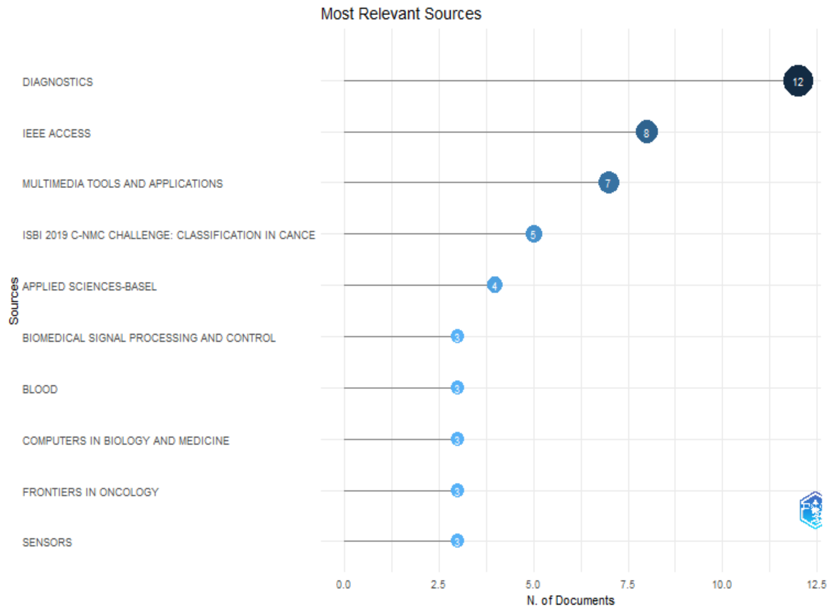

Figure 4. Ten most relevant sources.

4.6 Most relevant affiliations

Table 5. presents institutes related to the Classification of Acute Lymphoblastic Leukemia Deep learning publications from 2009 to 2023. Sichuan University came first with 19 publications, followed by Johns Hopkins University with 14 and Shandong University with 14.

Table 5. The ten most relevant affiliations

Affiliation	Country	Number of publications	Percentage
SICHUAN UNIVERSITY	CHINA	19	3.04%
JOHNS HOPKINS UNIVERSITY	UNITED STATE	14	2.24%
SHANDONG UNIVERSITY	CHINA	14	2.24%
ZHEJIANG UNIVERSITY	CHINA	13	2.08%
COMSATS UNIV ISLAMABAD	PAKISTAN	10	1.60%
UNIVERSITY TEKNOL MALAYSIA	MALAYSIA	10	1.60%
UNIVERSITY MILANO	ITALY	9	1.44%
National Institute of Technology	INDIA	8	1.28%
ASSIUT UNIVERSITY	EGYPT	7	1.12%
PRINCESS NOURAH BINT ABDULRAHMAN UNIVERSITY	SAUDI ARABIA	7	1.12%

4.7 Most frequent keywords

The word cloud figure displays the intensity of the occurrence of authors' keywords (Figure 3). In contrast, Figure 5 depicts the most frequent words together with the median year that the word appears, with the word "classification" (37) being the most frequent word, followed by "diagnosis" (22) and "segmentation" (18).

Figure 5. Most frequent words.

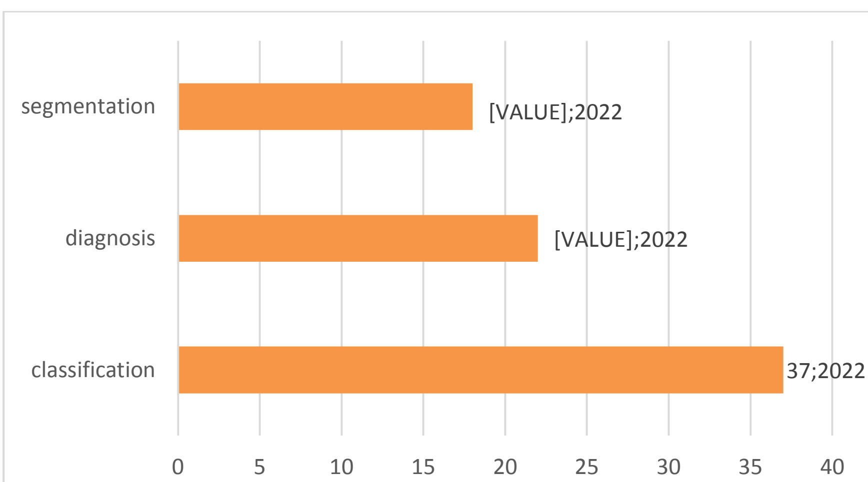

Figure 6. Most frequent word (frequency; median year)

4.7 Co-authorship network analysis:

The data retrieved from the Web of Science revealed that 654 distinct authors wrote the identified documents. The analyses of co-authorship are displayed in Figure 7.

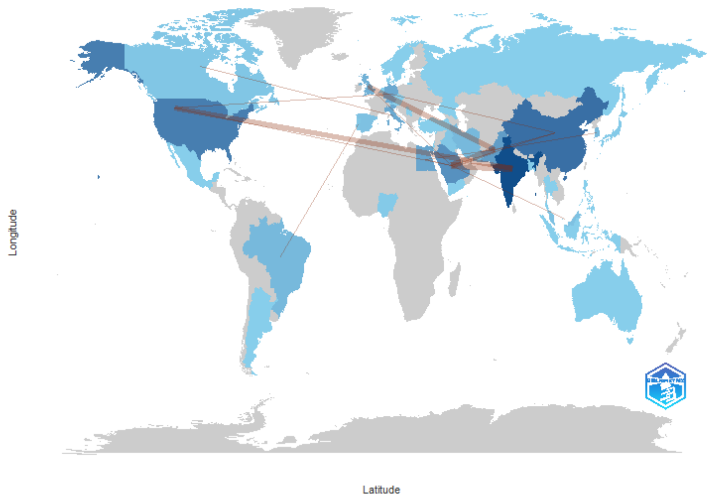

Figure 7. Co-authors' network analysis.

5. DISCUSSION

This study conducted a bibliometric analysis to examine the landscape of deep learning-based classification of Acute Lymphoblastic Leukemia (ALL) within the Web of Science database from 2009 to 2023. Our findings offer valuable insights into various aspects of this domain:

- **Growing Interest:** The observed increase in publications (Fig. 2) reflects a rising research interest in deep learning-based classification of ALL.
- **Theoretical Foundations:** High citation counts (Table 1) indicate the influence of foundational concepts and practical applications in this field.
- **Global Collaboration:** Network analysis (Fig. 3) reveals strong collaborative efforts among researchers. However, further investigation into collaboration patterns across diverse regions would be beneficial.
- **Citation Impact:** India leads in total citations (Table 3), while Brazil's higher average citations per publication suggest quality considerations beyond sheer volume. Exploring

factors influencing citation impact across regions could provide valuable insights.

- **Thriving Themes:** Word frequency analysis (Fig. 5) highlights key themes like classification, diagnosis, and segmentation alongside emerging areas such as "deep learning" and "artificial intelligence." Examining the evolution of these themes over time could reveal shifting research priorities.

Limitations and Future Directions:

The advent of deep learning has transformed the classification and diagnosis of ALL, offering unprecedented accuracy and efficiency. However, several limitations persist, necessitating ongoing research to address these challenges.

- Data Scarcity: Deep learning models require large, annotated datasets. The scarcity of such datasets often leads to models that lack generalizability.
- Heterogeneity of ALL: The diverse genetic and phenotypic subtypes pose significant challenges for creating robust models.
- Explainability: Deep learning models need to be interpretable to ensure that medical practitioners can trust and understand the decision-making process of these systems.
- Database Scope: Excluding other databases (e.g., Scopus) limits the comprehensiveness of the analysis. Future studies could benefit from a broader data spectrum.
- Quality Assessment: Citation counts are valuable indicators but do not capture all aspects of research quality. Future studies could incorporate additional quality metrics like peer review ratings or altimetric.
- Granularity: Analyzing sub-fields could reveal more nuanced trends and variations in research focus.

Implications for Researchers and Organizations:

This study provides a baseline understanding of the historical progression and current state of research in deep learning-based classification of ALL.

- Identifying prominent topics and emerging themes can inform researchers' decision-making in choosing avenues for exploration.
- Understanding collaboration patterns and identifying influential scholars can facilitate knowledge exchange and potential research partnerships.
- Recognizing gaps and under-researched areas can guide future research agendas and contribute to advancing the field.

By addressing these limitations and pursuing these future directions, the deep learning-based classification of ALL can advance significantly, leading to improved diagnostic accuracy and better patient outcomes.

6. CONCLUSION

In conclusion, this comprehensive bibliometric analysis, exploring the deep learning-based classification of Acute Lymphoblastic Leukemia (ALL) within the Web of Science database from 2009 to 2023, provides valuable insights for scholars and practitioners in this dynamic field. The increase in publications highlights the growing academic interest and the rising efficacy of research in this crucial domain. Network analysis reveals India, China, and the United States as key collaborators, suggesting concentrations of high-quality research and potential avenues for international collaboration to foster knowledge exchange and diverse perspectives.

Word frequency analysis identifies emerging themes such as "diagnosis," "classification," and "segmentation," reflecting a heightened focus on measuring and achieving positive outcomes. While this study offers valuable insights, it is limited to the Web of Science database. Future research could expand the scope by including additional databases and extending the timeframe for a more comprehensive perspective. Addressing potential limitations of bibliometric methods, such as publication bias or incomplete data coverage, would further enhance the study's robustness.

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