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RESEARCH ARTICLE

Bibliometric Analysis Of Machine Learning Applications In EEG For Epileptic Seizure Diagnosis Using Biblioshiny: Trends And Conceptual Structures

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Abstract. *This study examines the research landscape of machine learning applications in EEG-based epileptic seizure diagnosis through bibliometric analysis. A total of 2,805 Scopus-indexed publications (1967–2024) authored by 9,003 researchers were analysed using Biblioshiny in R-Studio to explore publication trends, influential works, collaboration networks, and thematic developments. The analysis reveals a steady annual growth rate of 1.91%, with a significant increase in research activity after 2015 driven by advancements in deep learning techniques. While the field benefits from an average of 5.4 co-authors per document, international collaboration remains modest at 26.2% of the total output. Support vector machines (SVMs), artificial neural networks (ANNs), and convolutional neural networks (CNNs) are widely used for seizure detection. However, challenges remain, including limited dataset diversity, real-world implementation barriers, and computational demands. The study finds that research output is concentrated among a few highly cited authors and journals, with fewer contributions from resource-limited regions. The findings indicate a need for broader collaborations, diverse datasets, and evaluation metrics that reflect clinical relevance rather than solely technical performance. Future research should explore explainable AI (XAI), wearable EEG technologies, and practical machine learning integration in clinical settings to improve accessibility and reliability. Addressing these challenges can enhance the impact of machine learning in EEG-based epilepsy diagnosis, leading to better patient outcomes. This bibliometric study provides a detailed, quantified overview of the field's progress, offering insights that can guide future research towards greater inclusivity, collaboration, and real-world applicability.*

1. Introduction

Epilepsy is one of the most prevalent neurological disorders globally, impacting an estimated 50 million individuals [1]. Characterised by recurrent, unpredictable seizures, epilepsy significantly disrupts the daily lives of those affected, often leading to social, psychological, and economic challenges. The disorder does not only affect patients but also places a considerable burden on their families and healthcare systems. As such, understanding its underlying mechanisms and developing effective strategies for diagnosis and treatment are crucial to improving the quality of life for individuals living with epilepsy. A key tool in the diagnosis and management of epilepsy is the electroencephalogram (EEG), a non-invasive technique that records the electrical activity of the brain. EEG plays a fundamental role in identifying abnormal brain patterns associated with epileptic events, making it a cornerstone in epilepsy research and clinical practice [2–4]. The intricate nature of EEG data presents significant challenges in interpretation, even among experienced clinicians. Variability in readings can lead to inconsistent diagnoses and potential misclassification of epilepsy [5]. To address these challenges, researchers are increasingly turning to machine learning techniques. These methods offer the potential to enhance the accuracy and consistency of EEG analysis, thereby improving the diagnosis and management of epilepsy [6].

Recent advancements in computational methods, particularly machine learning, have transformed the landscape of EEG signal analysis. Machine learning techniques are increasingly being employed to automate the detection of seizure patterns, offering a higher level of precision and reducing the chances of misinterpretation [7]. These methods enable the development of predictive models that can anticipate seizure onset, providing an opportunity for early intervention and improved management strategies for patients with epilepsy. Neural networks and deep learning algorithms, in particular, have demonstrated substantial success in capturing the intricate patterns within EEG data that traditional analysis methods often overlook [8, 9].

Despite these successes, the clinical adoption of deep learning models is frequently hindered by their "black box" nature, where the decision-making process remains opaque to healthcare providers. To resolve this, the field of Explainable AI (XAI) has emerged as a critical solution, providing frameworks that enhance transparency and allow clinicians to interpret how specific EEG features contribute to a model's output. By fostering trust through interpretability, XAI serves as a bridge between high-performance technical innovation and real-world clinical application.

The integration of machine learning and XAI into EEG analysis represents a promising direction for enhancing diagnostic accuracy and tailoring patient-specific treatment approaches. However, the rapid growth in this area of research has led to a large volume of literature, making it challenging for researchers to identify the most influential works, emerging trends, and knowledge gaps. Therefore, a systematic and quantitative approach, such as bibliometric analysis, is essential to organise and interpret this expanding body of research.

Bibliometric analysis serves as a powerful tool for mapping the development of a research field. By analysing publication trends, citation patterns, and collaboration networks, it provides valuable insights into the intellectual structure and dynamics of scientific research [10]. In the context of machine learning applications in EEG analysis for epilepsy, bibliometric analysis can help identify key studies, influential authors, and significant trends that have shaped the field's evolution. This approach not only aids in recognising established knowledge but also identifies emerging topics and future directions, providing guidance for researchers exploring this multidisciplinary area. The primary goal of this study is to conduct a comprehensive bibliometric analysis to understand the research landscape of machine learning applications in EEG signal analysis for epileptic seizure diagnosis. The study focuses on three key objectives:

1. To identify central articles that have significantly shaped the research landscape of machine learning applications in EEG for epileptic seizure diagnosis.
2. To explore the evolution of scientific production and country-specific research output, with an emphasis on identifying emerging trends and key contributors to the field.
3. To assess the contributions of leading authors and journals in advancing the field, based on their impact metrics and their role in guiding scholarly discussions. The study evaluates the influence

of authors and journals using H-index and citation metrics to understand their role in shaping research developments in machine learning and EEG research.

This study employs the Biblioshiny package from R-Studio to carry out the bibliometric analysis, using a dataset that spans 2,805 publications from 1967 to 2024. The analysis includes a detailed examination of publication patterns, author collaborations, keyword networks, and citation dynamics, providing a nuanced view of the research landscape. The paper is organised as follows: the Literature Review section examines prior studies on machine learning applications in EEG analysis, setting the context for the current analysis. The Methodology section outlines the data collection process and bibliometric methods, detailing the use of the Biblioshiny package. The Results and Analysis section presents the findings of the bibliometric study, focusing on three areas: identifying influential articles, analysing research trends, and evaluating the impact of key authors and journals. The Discussion section interprets these findings, exhibiting their implications for future research and clinical applications. The Limitations and Future Research Directions section discusses the study's constraints and suggests potential areas for further exploration. Finally, the Conclusion summarises the study's key contributions, reflecting on the insights gained from the bibliometric analysis and their relevance to the field of machine learning applications in EEG signal analysis for epileptic seizure diagnosis.

2. Literature Review

Recent advancements in epileptic seizure diagnosis have been largely driven by incorporating machine learning techniques into EEG data analysis. Researchers have increasingly focused on developing more accurate and predictive models to enhance seizure detection and management. This growing interest is evident in the expanding body of studies exploring these approaches. Methods such as deep learning models, including convolutional neural networks (CNNs), support vector machines (SVMs), and recurrent neural networks (RNNs), have played a pivotal role in improving diagnostic precision. For example, Gramacki and Gramacki [11] proposed a deep learning framework for detecting seizures in neonatal EEG signals, offering significant progress in automating the detection process with CNNs. Their work addresses reproducibility concerns by providing detailed methodologies and implementation codes for EEG-based seizure detection.

The impact of these advancements is reflected in citation trends, where studies on machine learning applications in EEG analysis are frequently referenced. Foundational contributions, such as those by Mirowski et al. [12] and Acharya et al. [13] are often recognised for shaping the field of automated EEG analysis, demonstrating the importance of data-driven techniques in improving diagnostic outcomes. Similarly, Roy et al. [14] provide a comprehensive review of deep learning applications in EEG analysis, showcasing their effectiveness across various contexts, including seizure detection, thereby reinforcing their influence on the field. Another significant development in epilepsy research has been the rise of personalised medicine. Customised approaches to analysing EEG data have shown promise in improving seizure management by tailoring interventions to individual patients. For instance, Tsiouris et al. [15] demonstrated the effectiveness of long short-term memory (LSTM) networks in predicting seizures, while Birjandtalab et al. [16] achieved effective detection using limited-channel EEG data, a practical solution for resource-constrained settings.

Collaborative research has also gained momentum, with more multi-institutional and international studies addressing epileptic seizure diagnosis. Antoniades et al. [17], for example, advanced the field by applying deep learning frameworks specifically to intracranial EEG data, leveraging sophisticated analytical techniques. These efforts reflect a collective initiative to pool expertise and resources to tackle the complexities of neurological disorders. Despite these strides, challenges remain. A key issue is the limited generalisability of machine learning models across diverse patient populations. Studies often rely on data from specific groups, which may not adequately represent broader populations. Faust et al. [18] stress the need for large, diverse datasets to make deep learning models more adaptable to healthcare applications, including EEG-based seizure prediction. Another challenge lies in transitioning these models from controlled research settings to clinical practice. Variability in data, signal noise, and computational demands pose significant obstacles. Mormann and Andrzejak [19] discuss these hurdles and advocate for creating models that are both interpretable and adaptable to clinical workflows. Acharya et al. [20] also argue for developing robust predictive solutions that can handle the complexities of real-time medical data.

The trend toward personalised healthcare in epilepsy research continues to gain traction. Approaches that analyse individual EEG patterns are proving valuable in advancing seizure management. Craik et al. [21] explored how combining machine learning with wearable technology could significantly enhance patient-specific treatment strategies, showcasing the potential of real-world data in advancing precision medicine. Advanced algorithms such as CNNs and LSTM networks have been particularly effective in identifying subtle EEG patterns that signal imminent seizures. Sharan and Berkovsky [22] demonstrated how multi-channel EEG wavelet power spectra and 1-D CNNs could achieve high detection accuracy, further supporting the value of patient-tailored methods. Moreover, Islam et al. [23] called for standardising EEG monitoring techniques to ensure consistent data quality, a crucial factor for accurate seizure detection.

Bibliometric analysis has become an essential tool for assessing research progress and impact across scientific disciplines. By examining publication trends, citation patterns, and collaborative networks, this approach provides a structured overview of how a research field evolves. In studying machine learning applications for EEG analysis in epilepsy, bibliometric analysis reveals significant contributions and emerging trends. This study applies bibliometric methods to address gaps in machine learning and EEG analysis for epilepsy research. By examining influential works and collaborative networks, the analysis identifies opportunities for interdisciplinary and international partnerships, which are vital for advancing the field. For example, Zupic and Čater [24] found that strong research networks often lead to high-impact contributions. By offering a comprehensive overview of research trends and pinpointing areas that require further exploration, this analysis aims to guide future studies and promote progress in epileptic seizure diagnosis using machine learning techniques.

This study tends to achieve the following research objectives:

1. To identify central articles that have significantly shaped the research landscape of machine learning applications in EEG for epileptic seizure diagnosis.
2. To explore the evolution of scientific production and country-specific research output, with an emphasis on identifying emerging trends and key contributors to the field.
3. To assess the contributions of leading authors and journals in advancing the field, based on their impact metrics and their role in guiding scholarly discussions.

3. Methodology

3.1. Bibliometric research

The bibliometric research method is a tool used to map relationships between disciplines, research fields, scholars, and individual publications [24]. This method has become popular among researchers because it helps to organize and visualize the structure of a scientific field, making it easier to understand research trends and connections [25]. By using data from scientometric databases, bibliometric analysis provides a systematic way to review literature and identify key patterns in research. In this study, bibliometric analysis was applied to examine publications on machine learning applications in EEG signal analysis for epileptic seizure diagnosis. The focus was on identifying influential studies, understanding emerging trends, and assessing contributions from leading authors.

3.2. Data Collection

The primary bibliometric indicators for this study, as summarized in Figure 1, were derived from a corpus of 2,805 documents retrieved from the Scopus database on 9 October 2024. To ensure a reproducible capture of the research landscape, the search targeted titles, abstracts, and keywords using the Boolean search string detailed in Appendix 1. Although the initial retrieval encompasses a chronological span from 1967 to 2025, a strategic distinction is maintained between the total dataset and the annual growth analysis to ensure temporal accuracy. While the dataset includes "Early Access" and "Ahead of Print" articles officially assigned to the 2025 volume year, longitudinal visualizations primarily emphasize trends through the last complete calendar year, which is 2024. This approach prevents a misleading representation of research output for the final, incomplete period.

Figure 1. Summary of bibliometric indicators and dataset characteristics.

The final corpus involves 9,003 researchers across 675 sources, reflecting a steady annual growth rate of 1.91%. On average, each document contains 5.4 co-authors, and 26.2% of the publications involve international collaboration. These metrics, alongside an average of 32.93 citations per document, indicate significant scholarly engagement and a globalized research effort in the field of EEG-based seizure diagnosis.

3.3. Data Screening and Cleaning

The data screening protocol was established to secure a high-quality, peer-reviewed corpus suitable for longitudinal impact analysis. Selection criteria were restricted to journal articles and "Early Access" publications officially dated for 2025 that were indexed at the time of the October 2024 search. Although conference proceedings frequently disseminate significant advancements in machine learning, they were excluded, alongside books, editorials, and letters, to prioritize sources subjected to a standardized and rigorous journal-tier peer-review process. Methodologically, excluding conference papers reduces "noise" from preliminary or duplicate findings that are often expanded into full journal articles later. This precaution ensures that bibliometric metrics, such as the H-index and Local Citations, are not artificially inflated by multiple versions of the same study, thereby providing a more accurate representation of established scientific impact.

3.4. Data Analysis

Data analysis was conducted using the Biblioshiny package from R-Studio, a powerful tool designed for comprehensive bibliometric and scientometric studies. This package allows for the systematic examination and visualization of the research landscape through several distinct lenses.

3.4.1. Central Articles

The analysis begins by identifying the foundational works that have shaped the scholarly discourse on machine learning applications for EEG-based epileptic seizure diagnosis. This is achieved by calculating three primary metrics: Most Global Cited Documents, Most Local Cited Documents, and Most Local Cited References. Global citations represent the total number of citations a document has received across the entire Scopus database, indicating its broad academic visibility. In contrast, local citations measure the impact of a document strictly within the 2,805 publications included in this study's specific dataset. By comparing these metrics, the study distinguishes between works with general scientific influence and those that form the specific intellectual core of the EEG-ML seizure diagnosis field.

3.4.2. Evolution of Scientific Production

To explore the growth and geographic distribution of the field, the study analyzes annual scientific production and country-specific research output over time. These metrics track the volume of publications from 1967 to 2025 to identify major shifts in academic interest. Because the data for late 2024 and 2025 was only partially available at the time of the search (October 2024), these years are interpreted as indicators of current momentum rather than finalized annual totals. This longitudinal perspective helps visualize the acceleration of research activity, particularly following advancements in computational power and deep learning.

3.4.3. Leading Authors and Journals

The final stage of the analysis assesses the influence of key authors and journals using impact metrics such as publication volume and the H-index. This process identifies the most relevant sources for research dissemination and the most prolific authors within the domain. The H-index is utilized here as a measure of an author's sustained scholarly presence and citation impact within the academic community. These results provide a structured overview of the intellectual hierarchy of the field, highlighting the venues and individuals most central to guiding contemporary scholarly discussions. Table 1 provides an overview of the research questions, the strategies employed, and the analysis techniques used to address them.

Table 1. Summary of research questions, strategies, and results used.

RO	Description	Strategy to Answer RQ	Results Used
1	To identify central articles that have significantly shaped the research landscape of machine learning applications in EEG for epileptic seizure diagnosis.	Analyse the most cited documents (globally and locally) to uncover the foundational works and key concepts that have influenced ongoing research directions.	Most Global Cited Documents, Most Local Cited Documents, Most Local Cited References
2	To explore the evolution of scientific production and country-specific research output, with an emphasis on identifying emerging trends and key contributors to the field.	Examine annual scientific production trends and country-specific research output over time to identify shifts in research focus and emerging areas of interest.	Annual Scientific Production, Country Production Over Time, Country Scientific Production
3	To assess the contributions of leading authors and journals in advancing the field, based on their impact metrics and their role in guiding scholarly discussions.	Evaluate the impact of authors and journals using H-index and citation metrics to determine their influence in shaping research developments.	Author Impact, Most Relevant Authors, Most Relevant Sources, Source Impact

4. Results

4.1. Most Globally Cited Documents

Figure 2 illustrates the most globally cited studies shaping the research landscape of machine learning in EEG-based seizure diagnosis. In this visualization, the vertical axis lists the documents identified by the first author and year, while the horizontal axis represents global citations, defined as the total citation count a document has received across the entire Scopus database.

Subasi et al. [26, 27], both published in Expert Systems with Applications, dominate with 982 and 967 citations, respectively. These studies introduced methodologies leveraging Support Vector Machines (SVMs) and Artificial Neural Networks (ANNs), forming a foundation for subsequent advancements in seizure detection. However, while foundational, these studies do not fully address the complex challenges of patient-specific EEG variability and real-time data analysis now central to the field. Cohen et al. [28] in Science (789 citations) contributed an interdisciplinary perspective, expanding machine learning's applicability beyond conventional domains. This indicates the integration of computational neuroscience and machine learning, yet raises questions about whether this breadth dilutes the epilepsy-specific focus. Similarly, Acharya et al. [13] in Knowledge-Based Systems (665 citations) represents a foundational contribution to automated EEG analysis, with its proposed methodologies frequently cited as benchmarks for improving diagnostic accuracy. Nonetheless, challenges persist due to limited dataset diversity, as evidenced in more recent studies. Other contributions, such as Tzallas et al. [29] in IEEE Transactions on Information Technology in Biomedicine (671 citations) and Irani et al. [30] in Annals of Neurology (719 citations), utilized wavelet transforms and computational approaches to enhance EEG analysis. While impactful, their slower citation trajectory suggests limited adoption into clinical workflows, emphasizing the gap between theoretical models and practical application.

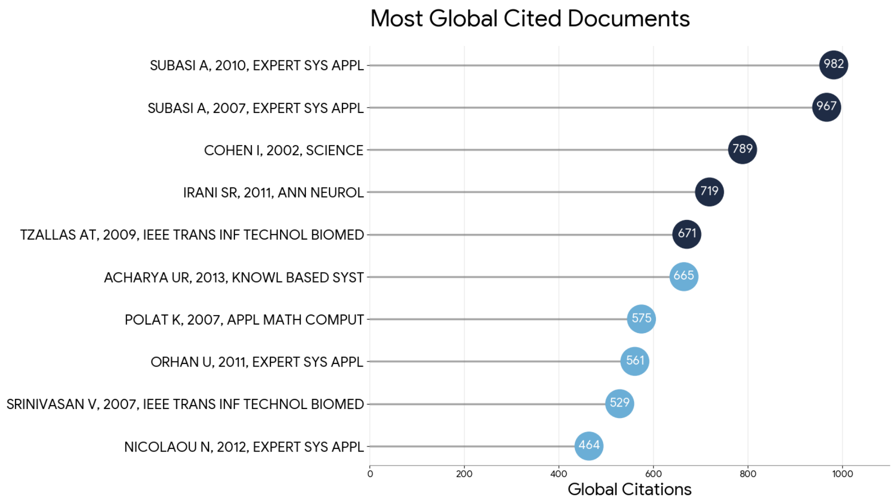

Figure 2. Most Globally Cited Documents

4.2. Most Locally Cited Documents

Figure 3 identifies publications that are highly cited within the local research context. In this visualization, the vertical axis lists the documents, categorized by the primary author and year of publication, while the horizontal axis represents local citation. This metric is calculated by enumerating the citations a specific document has received exclusively from other papers within the 2,805-document corpus analyzed in this study.

The study by Tzallas et al. [29], which received 183 local citations, has been instrumental in shaping regional research priorities. Its focus on wavelet transforms and automated signal analysis constitutes a foundational element of EEG research literature. However, despite its academic influence, the applicability of the study to practical clinical settings, particularly in low-resource environments, remains limited. This limitation highlights the necessity for subsequent research to adapt these methodologies to diverse healthcare contexts. Similarly, Acharya et al. [13], with 170 local citations, demonstrates significant scholarly relevance both globally and locally, suggesting that its methods, which are rooted in higher-order spectra analysis, possess robust adaptability within the academic discourse. Nevertheless, while these techniques are widely cited, the reliance on relatively controlled datasets presents challenges for generalizability across patient populations with varying demographic and clinical profiles. Addressing this limitation is essential for transitioning such foundational academic work toward potential clinical solutions.

Subasi et al. [26] and Truong et al. [31] also rank highly, reflecting the increasing adoption of deep learning models, such as convolutional neural networks (CNNs), and wavelet-based analysis.

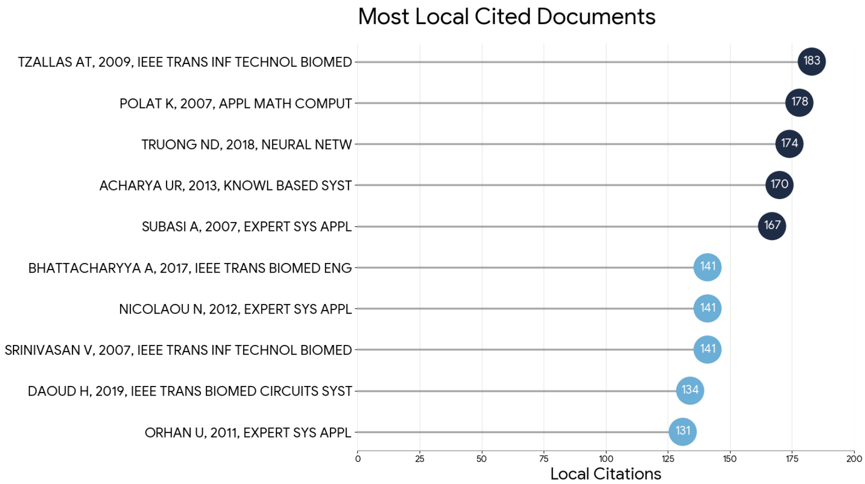

Figure 3. Most Locally Cited Documents

These methods have demonstrated potential in improving specificity and reliability in EEG-based applications. However, their computational requirements and scalability present significant challenges. For instance, implementing these models in resource-limited clinical settings or with real-time data remains an area requiring further development. This observation indicates a broader issue in the field; while high-accuracy results are frequently achieved in controlled research environments, practical deployment requires careful consideration of cost, infrastructure, and ease of integration. Moreover, these findings suggest a prevailing trend in local research, characterized by an emphasis on leveraging computational advancements without adequately addressing implementation barriers. A critical gap emerges here, as most locally influential studies prioritize refining algorithms rather than addressing clinical adoption. Future research must balance computational innovation with practical applicability to ensure that solutions are accessible and impactful across a broader range of healthcare environments.

4.3. Frequently Cited References

Figure 4 identifies the most frequently cited references that form the foundational basis for research in machine learning applications to EEG-based seizure detection. In this chart, the vertical axis represents the references cited within the corpus, while the horizontal axis indicates local citations, which measures the frequency with which a specific work appears in the reference lists of the 2,805 documents in our dataset. This visualization highlights the tiered influence of foundational studies, with most entries falling within the range of 50 to 80 local citations.

Among these, Shoeb [32], with 133 local citations, is highlighted as a pivotal study in the intellectual heritage of real-time seizure detection, showing a substantial lead over other foundational works such as Faust [33] and Acharya U.R. [20], which recorded 75 and 74 local citations, respectively. This research is frequently recognized in the literature for its focus on addressing essential challenges through machine learning algorithms. However, its broader implementation in clinical practice remains limited due to persistent obstacles. One significant issue is the inherent variability in EEG data, which may stem from differences in electrode placement, signal noise, or individual patient characteristics. Such variability constrains the algorithms' generalizability, emphasizing the academic need for models capable of adapting to diverse data conditions without compromising their predictive performance.

Acharya et al. [20] and Faust et al. [33] provided notable contributions to the development of neural network-based approaches and scalable EEG analysis systems. While these studies establish a robust theoretical framework, their practical impact is constrained by a lack of standardized

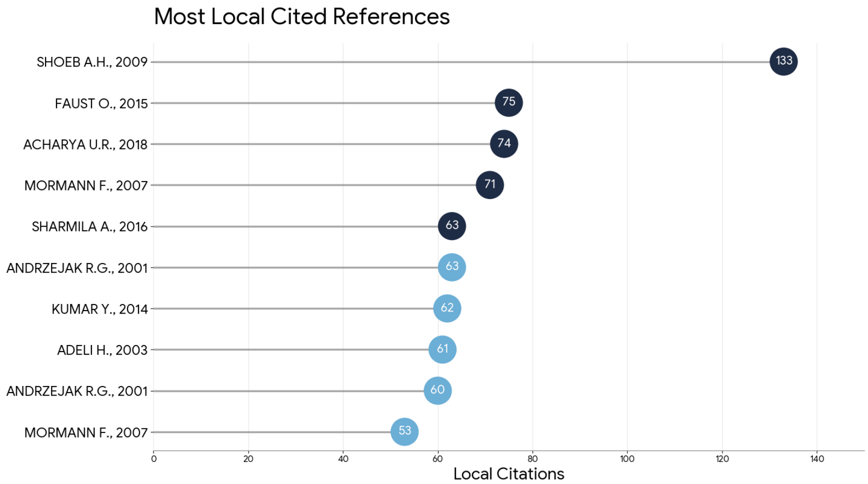

Figure 4. Most Locally Cited References

datasets. This deficit poses significant barriers to widespread adoption, as models trained on region-specific or institution-specific datasets may not perform reliably in heterogeneous settings. Moreover, the focus on scalability, although valuable, often overlooks the interpretability of these models, which remains an essential factor for clinician trust and adoption within healthcare environments. Mormann et al. [34] further elaborate on these limitations, emphasizing the necessity for solutions that balance scalability with clinical applicability. The study identifies a persistent gap in the field; while many algorithms achieve high accuracy in controlled research environments, their performance frequently declines in practical scenarios. This disparity highlights the requirement to incorporate diverse, representative datasets during model training and validation to ensure robustness and reliability.

4.4. Trends in Scientific Output and Country Contributions

4.4.1. Annual Scientific Production

The annual scientific production, as illustrated in Figure 5, demonstrates a substantial expansion in research output over the assessed period. The data reveals a steady increase in publications starting in the late 20th century, followed by a period of exponential growth after 2015. This trajectory reflects an intensified focus on machine learning applications within EEG signal analysis, likely catalyzed by the convergence of advanced deep learning algorithms and enhanced computational hardware. Furthermore, the accessibility of large-scale, open-source EEG datasets and increased research funding for neurological disorders have been instrumental in sustaining this momentum.

However, a sharp decline is visible in the production metrics for 2024 and 2025. It is critical to interpret this downward trend as a byproduct of the data collection timeline rather than a reduction in scholarly interest or productivity. Since the data extraction was conducted in October 2024, the records for that year represent only a partial annual cycle. Similarly, the 2025 data consists exclusively of “Early Access” and “Ahead of Print” publications indexed at the time of retrieval. Consequently, the observed drop-off is an artifact of real-time indexing lags and incomplete calendar years. When these preliminary periods are contextualized, the underlying trend confirms a continuing and robust trajectory of innovation in automated epileptic seizure diagnosis.

4.4.2. Country Production Over Time

Figure 6 illustrates the longitudinal growth of country-specific research output, where the horizontal and vertical axes represent the publication year and cumulative article count, respectively. The United States and China emerge as dominant contributors, exhibiting a consistent increase in scientific production. The high volume of US-based publications aligns with its extensive research

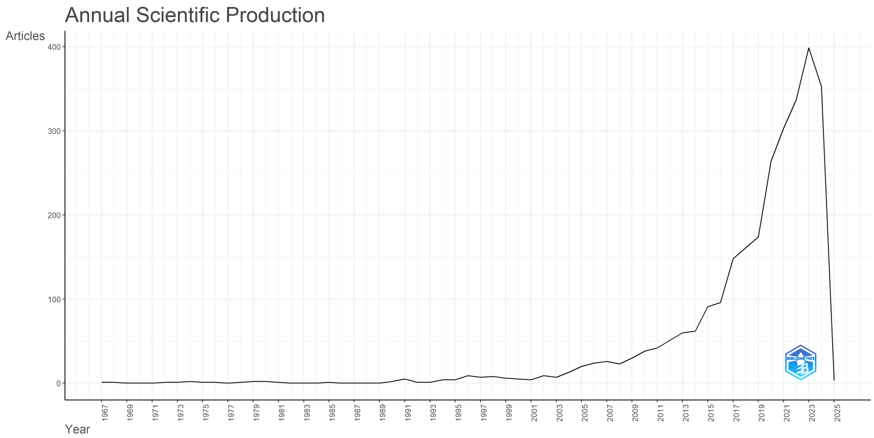

Figure 5. Annual scientific production trends illustrating longitudinal growth and recent data indexing limitations.

infrastructure, whereas the trajectory of Chinese output reflects an intensified academic focus on artificial intelligence and biomedical sectors. Although on a smaller scale, nations such as India, France, and Australia also demonstrate notable growth. This diversification suggests that the field is gaining global traction, necessitating international participation to address the complexities of EEG-based seizure diagnosis.

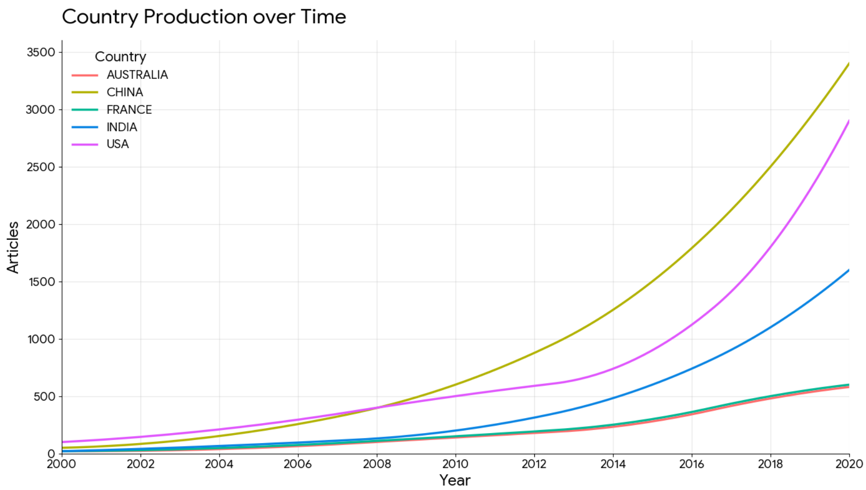

Figure 6. Country Production Over Time

4.4.3. Country Scientific Production

The analysis of global scientific production on machine learning applications in EEG for epileptic seizure diagnosis reveals significant disparities in research contributions across countries (Figure 7). The intensity of shading on the map indicates variations in output, with darker hues representing greater contributions. China and the United States stand out as the leading nations in this field, as indicated by the darkest shading on the map. These countries account for a substantial portion of global publications, reflecting their robust research infrastructure, significant funding, and longstanding investment in machine learning and neuroscience research [35]. Their leadership demonstrates the effectiveness of integrating interdisciplinary approaches, particularly in applying artificial intelligence to healthcare.

China's leadership can be attributed to strategic government initiatives that prioritize artificial

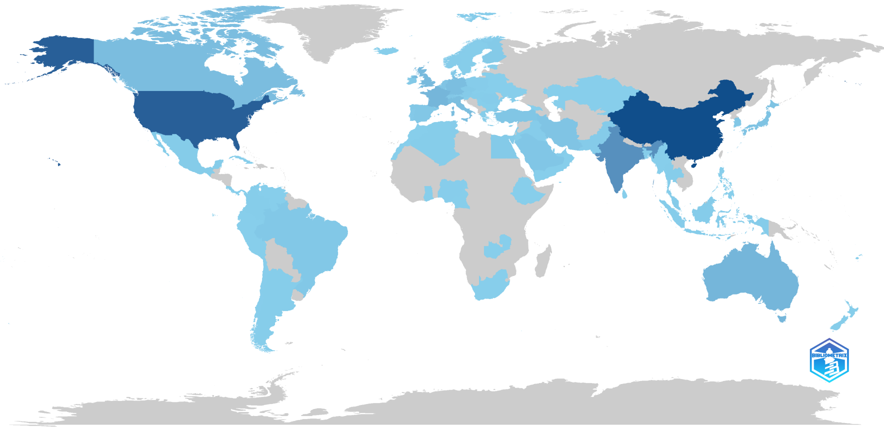

Figure 7. Country Scientific Production

intelligence (AI) and healthcare integration. The "New Generation Artificial Intelligence Development Plan" aims to position China as a global leader in AI by 2030, fostering substantial public investment in AI research and development across various sectors, including healthcare [36]. This strategic focus has led to significant advancements in applying machine learning techniques to EEG analysis for epileptic seizure diagnosis. Similarly, the United States maintains a leading position due to its extensive research ecosystem and substantial investments in AI [37]. The collaborative environment among academic institutions, industry, and government agencies has facilitated the development and application of machine learning in medical diagnostics, including EEG-based epilepsy detection. This integrated approach underscores the effectiveness of interdisciplinary collaboration in advancing healthcare technologies.

European countries exhibit a moderate yet widespread contribution to the field. Nations such as Germany, the United Kingdom, and France are notable contributors, likely due to their established academic frameworks and collaborative research initiatives. Similarly, in Asia, countries like India and Japan show notable activity, although their output remains secondary to China's. In Oceania, Australia emerges as the most significant contributor, reflecting focused efforts in machine learning research for healthcare applications. Latin America and Africa display limited contributions, with only a few countries involved in this area. Brazil and South Africa, for instance, are among the more active nations in their respective regions, but their research output remains relatively low compared to global leaders. This calls the need for targeted efforts to strengthen research capacity and foster collaboration in these underrepresented regions.

Countries with lighter shading, such as South Korea, Russia, and Brazil, represent emerging contributors to the field. Their growing engagement may be attributed to increasing governmental and institutional support for artificial intelligence research. With continued investment and collaborative opportunities, these nations have the potential to play a more significant role in the future of this field. The unequal distribution of research production reveals a concentration of expertise and resources in a few nations. This imbalance poses challenges for addressing region-specific issues, particularly in low-resource settings where the burden of epilepsy is often greater.

4.5. Key Authors and Journals in the Field

4.5.1. Authors' Impact by H-Index

In Figure 8, the vertical axis lists the leading Authors, while the horizontal axis represents the Impact Measure: H (H-index). This metric evaluates scholarly impact by balancing publication volume with citation frequency within the dataset. The H-index analysis shows that a small group of researchers consistently achieve high H-index scores, reflecting their sustained contributions over time.

Prominent figures such as Wang Y and Zhang Y have consistently produced influential work, with their studies cited across a broad range of research areas. These authors have played a key role in advancing both theoretical concepts and practical applications in EEG-based epilepsy diagnosis.

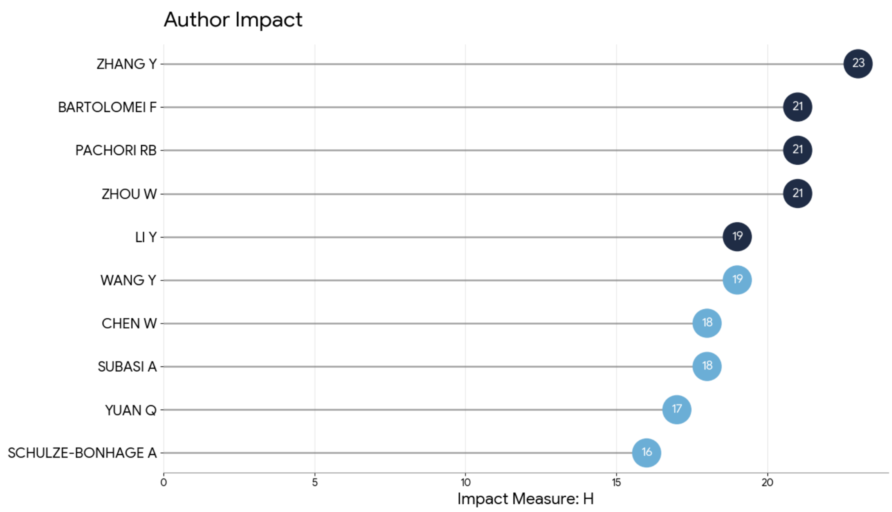

Figure 8. Authors' Impact by H-Index

Their work reflects both the breadth of their research topics and the lasting impact of their contributions. Similarly, Bartolomei F, Pachori RB, and Zhou W, each with an H-index of 21, have established themselves as leading contributors whose studies underpin critical advancements in EEG and machine learning applications. While these metrics demonstrate the influence of these authors, a deeper look is needed to determine whether their contributions are concentrated within specific subfields or have broader interdisciplinary applications. For instance, their high H-indices might be driven by a few highly cited seminal works. If their influence is reliant on these key publications, it could suggest that the field is highly focused on particular paradigms, potentially limiting exploration of alternative approaches.

Authors such as Li Y and Wang Y, with H-indices of 19, represent an important tier of contributors whose work plays a supporting role in advancing research. Their narrower scope of citations could indicate specialisation or early-stage contributions within the field. However, it raises questions about whether these authors are innovating in new directions or building upon established methodologies. Understanding their role is crucial to assessing how diversified the field is in terms of approaches and perspectives. Contributors with lower H-indices may reflect underexplored niches or emerging areas of research within EEG and machine learning. While they may not yet have widespread citations, these authors could be driving novel methodologies or addressing practical challenges that have not been the focus of dominant contributors. Evaluating their impact beyond citation metrics would help identify potential areas of innovation that are not immediately visible through traditional bibliometric measures.

4.5.2. Most Relevant Authors by Publications

As illustrated in Figure 9, authors such as Wang Y, Zhang Y, and Wang X dominate the publication landscape, with 54, 51, and 44 documents, respectively. In this chart, the vertical axis lists the leading Authors, while the horizontal axis represents the number of documents, indicating the total count of publications authored by each individual within the study's timeframe. Their contributions have consistently advanced methodological and practical innovations. These highly cited researchers have significantly impacted both theoretical developments and real-world applications, consolidating their positions as key figures in the field.

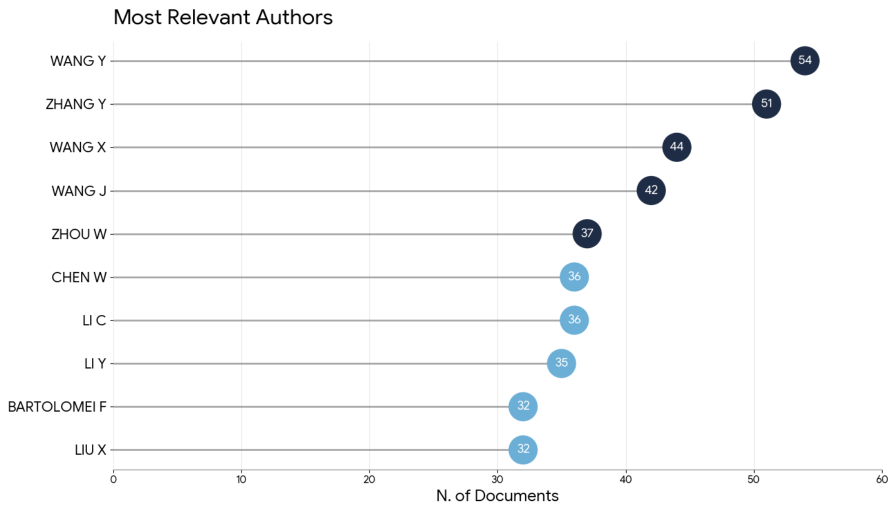

Figure 9. Most Relevant Authors

The prominence of these individuals reflects not only their productivity but also the broad applicability of their work. However, this concentration reflects a reliance on established figures, which may limit the diversity of perspectives and approaches in the domain. Encouraging emerging researchers to contribute and diversifying the range of voices in the field could enrich the discourse and lead to innovative solutions. The findings also reveal the value of collaboration, as many highly cited works are the result of interdisciplinary and international partnerships. These collaborations have successfully bridged gaps between engineering, neuroscience, and clinical medicine, leading to impactful contributions. Despite these advancements, the analysis shows underrepresentation from authors based in low- and middle-income countries. Such regions, which bear a disproportionate epilepsy burden, remain on the periphery of research contributions. Addressing this gap requires fostering inclusive collaborations and equitable resource distribution, which could diversify insights and enhance the global relevance of research.

4.5.3. Most Relevant Journals by Publications

The journal landscape, as depicted in Figure 10, reveals a distinct division between technical and clinical priorities in research dissemination. In this chart, the vertical axis lists the leading sources (journals), while the horizontal axis represents the number of documents, indicating the total number of articles published by each source within the dataset.

Biomedical Signal Processing and Control, with 119 publications, serves as a primary venue for technical contributions, particularly those emphasizing algorithmic advancements and signal-processing methodologies. While this highlights the field's strength in machine learning development, the journal's dominance suggest a significant focus on technical innovation compared to integrated clinical applications. Clinical journals such as ***Epilepsia*** (83 publications) and ***Annals of Neurology*** (82 publications) are essential for applying research outcomes to epilepsy management. However, their lower publication counts relative to technical journals point to a persistent gap in translating machine learning developments into practical, patient-centric solutions. This imbalance may be attributed to the complexity of integrating advanced models into clinical workflows or limited collaboration between technical and medical research communities.

Engineering-focused journals like ***IEEE Transactions on Biomedical Engineering*** and ***IEEE Transactions on Neural Systems and Rehabilitation Engineering*** (65 and 64 publications, respectively) further indicates the technical emphasis of the field. While these platforms advance methodological rigor, they might inadvertently restrict accessibility for clinicians and researchers from non-

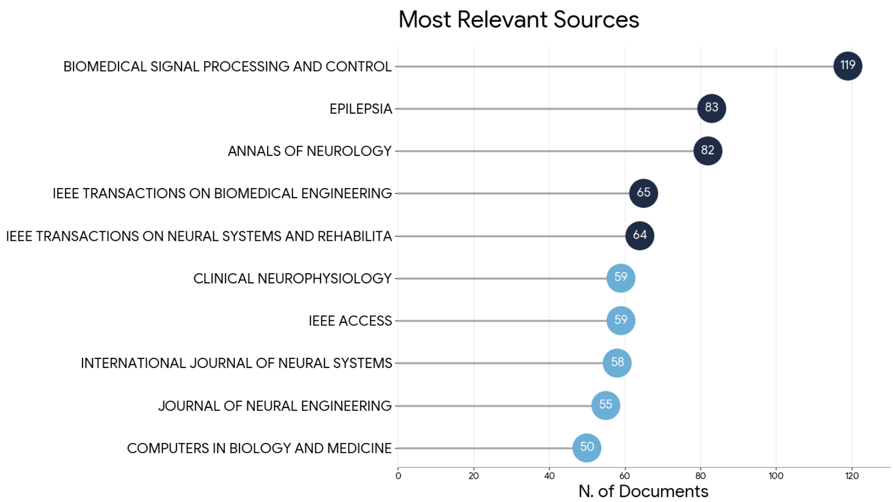

Figure 10. Most Relevant Sources

engineering backgrounds. As a result, potentially impactful research may remain confined to technical discussions, slowing its adoption in clinical practice. The limited representation of clinical journals also suggests that research priorities may not adequately address the pressing needs of healthcare professionals and patients. For example, while significant efforts are directed toward optimising algorithms, there is less emphasis on validating these models in diverse patient populations, addressing ethical concerns, or ensuring usability in real-world clinical settings. This disconnect risks creating highly specialised solutions that lack broader applicability or fail to align with clinical priorities.

A further consideration is the siloed nature of research publishing. With technical and clinical journals catering to distinct audiences, there may be insufficient cross-disciplinary dialogue. This separation could hinder the holistic development of solutions that are both technically robust and clinically relevant. Encouraging publication in multidisciplinary journals or fostering collaborations that target integrated research goals could help bridge this divide. To address these challenges, researchers should prioritise collaborative studies that focus on clinically meaningful outcomes, ensuring that technical advancements align with healthcare needs. Additionally, journals could play a proactive role by encouraging interdisciplinary submissions and promoting special issues that integrate technical innovations with clinical validation. By expanding the focus beyond technical developments and fostering partnerships with clinicians, the field can better advance machine learning applications for EEG analysis in real-world settings.

4.5.4. Impact of Sources in Driving Scholarly Contributions

The influence of key sources shown in Figure 11 plays a pivotal role in shaping the trajectory of research within machine learning applications for EEG-based epilepsy diagnosis. In this visualization, the vertical axis lists the leading sources (journals), while the horizontal axis represents the immpact measure (H-index), which quantifies the citation impact and productivity of these publications within the analyzed field.

An analysis of the most influential journals reveals their substantial impact in disseminating foundational and innovative studies. The high H-index of *Annals of Neurology* ($H = 37$) reflects its prominence as a venue where clinical and technical research intersect, indicating significant scholarly attention toward applied neurology. This prominence highlights the necessity of clinically focused contributions that align research outputs with practical healthcare challenges. However, its dominance also signals a need to assess whether the journal provides adequate space for technical innovation or primarily favors applied studies.

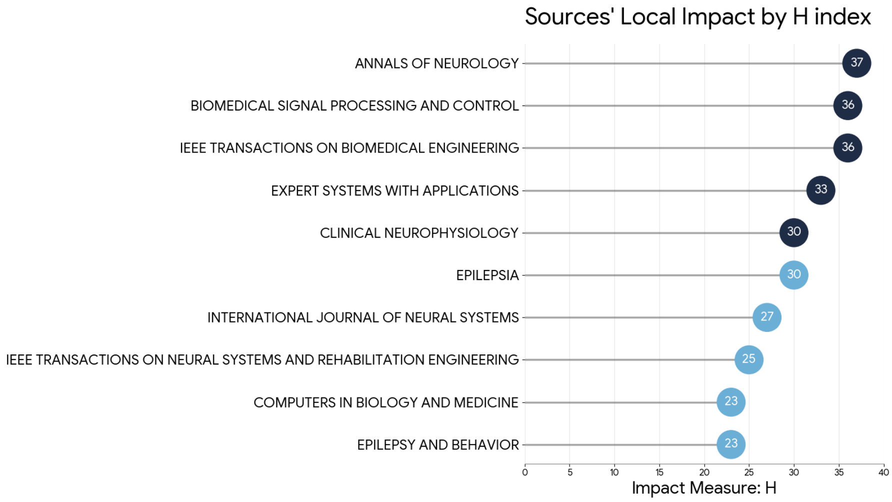

Figure 11. Sources' Local Impact by H-Index

Biomedical Signal Processing and Control ($H = 36$), another high-ranking source, plays a critical role in publishing algorithmic and signal-processing innovations. This reflects the field's emphasis on developing advanced computational methods, though it raises questions regarding the translation of these contributions into practical clinical tools. The similarly high H-index of *IEEE Transactions on Biomedical Engineering* ($H = 36$) attests to its influence in advancing technical rigor, yet the focus on engineering may limit accessibility to a broader clinical audience.

Journals such as *Expert Systems with Applications* ($H = 33$) and *Clinical Neurophysiology* ($H = 30$) demonstrate their importance in specific niches within the field. The former focuses on the application of expert systems, such as artificial intelligence, to practical problems, making it a valuable platform for presenting innovative use cases. The latter emphasizes neurophysiological research, ensuring that technical advancements remain relevant to neurological applications.

However, the relatively lower H-indices of clinically oriented journals, such as *Epilepsia* ($H = 30$), suggest that translating technical research into clinical practice remains a challenge. Smaller contributors, including *Computers in Biology and Medicine* and *Epilepsy and Behavior* (both with H-indices of 23), represent more focused platforms. These journals cater to interdisciplinary research and niche applications, which are vital for addressing specific aspects of epilepsy diagnosis and management. Their lower H-index values do not necessarily reflect lower quality, but rather their specialized scope or limited audience reach.

5. Discussion

The findings presented in the previous section reveal significant trends, contributions, and challenges in the application of machine learning to EEG-based epileptic seizure diagnosis. While notable advancements have been achieved, a critical examination identifies areas where progress is concentrated and opportunities for further improvement remain.

It is essential to note that the high citation counts and publication volumes identified in this study reflect scholarly interest and the "intellectual ancestry" of the field rather than the verified clinical efficacy of specific algorithms. While foundational works dominate the citation landscape, this prominence indicates their role as methodological benchmarks in academic research. The transition from high-impact scholarly work to validated clinical tools requires empirical evidence and longitudinal patient outcomes, which lie beyond the scope of this bibliometric analysis.

The period post-2016 witnessed substantial progress in machine learning and deep learning methodologies, particularly the adoption of deep neural networks for complex data analysis. These trends in the literature suggest that researchers are increasingly prioritizing the processing and interpretation of EEG signals to address diagnostic challenges. For instance, Kunekar et al. [38] proposed deep learning techniques to automate feature extraction and classification, a methodology that has since become a focal point for studies aiming to enhance diagnostic precision. This era also saw a surge in computational power and the availability of extensive EEG datasets, which facilitated the training of sophisticated models. Handa et al. [39] reviewed AI-based pipelines for automatic epilepsy diagnosis, noting that the literature increasingly reports reductions in introspection time without compromising algorithmic accuracy.

There has been a parallel recognition in the literature of the potential for AI to support healthcare, particularly in neurology. The convergence of machine learning with EEG and MRI data has opened new avenues for research into real-time seizure diagnosis and personalized treatment plans, as discussed by Rehab et al. [40]. Enhanced funding opportunities and interdisciplinary collaborations have further fostered innovation. Kerr and McFarlane [41] clarified the expanding role of machine learning in epilepsy, emphasizing its potential utility in assisting clinical decision-making.

The results indicate that a small group of authors and journals dominate the field. Authors such as Zhang Y and Wang Y, with high productivity and citation metrics, have significantly influenced the research landscape. While their contributions provide stability and continuity, this concentration raises questions regarding the diversity of approaches. Overreliance on a select group of contributors may limit opportunities for innovation and reduce representation from underexplored contexts.

A central theme emerging from this analysis is the disconnect between technical innovation and clinical application. Technical journals like *Biomedical Signal Processing and Control* dominate the landscape, while clinically focused outlets such as *Epilepsia* remain underrepresented. This disparity reflects a broader issue of insufficient interdisciplinary collaboration. Many technical contributions focus on algorithmic sophistication, yet practical concerns such as model interpretability through Explainable AI (XAI), usability in diverse populations, and integration with existing healthcare workflows are less frequently the primary focus of highly cited works. This disconnect risks slowing the adoption of machine learning tools in real-world epilepsy management and highlights the need for stronger partnerships between technical and clinical researchers.

The findings also reveal an underrepresentation of contributions from low- and middle-income countries (LMICs), despite these regions bearing a significant share of the global epilepsy burden. Beyond general funding constraints, specific institutional limitations hinder research output in these regions. These include a critical scarcity of high-performance computing (HPC) infrastructure necessary for training complex deep learning models and a lack of localized, open-access clinical datasets. Most major EEG datasets originate from high-income countries, creating a “data bias” where algorithms may not generalize effectively to diverse global populations due to variations in genetic or environmental factors. Furthermore, the limited availability of specialized training programs often prevents the formation of effective interdisciplinary teams combining engineering and clinical expertise. Addressing these structural barriers requires targeted policy interventions, such as international capacity-building partnerships and the establishment of regional data repositories, to ensure that machine learning solutions are both equitable and effective globally.

Moreover, citation-based metrics like the H-index may inadvertently exacerbate this disconnect. While these metrics effectively measure academic influence, they do not capture the practical or societal relevance of a study. Expanding evaluation frameworks to include criteria such as translational success and patient-centred outcomes would provide a more holistic understanding of a study’s contributions.

In summary, the field has demonstrated significant progress in technical and methodological advancements, yet challenges in clinical translation, regional representation, and interdisciplinary collaboration remain visible in the publication data. Addressing these gaps will be essential for ensuring that research efforts align with the goal of impactful, patient-centred outcomes.

6. Implications

Following the analysis of the bibliometric findings, this section explores the broader suggestions for advancing research discourse in the field. The insights gained emphasize an academic need for greater diversity in contributions and stronger interdisciplinary frameworks to bridge technical literature with clinical research needs.

6.1. Theoretical Implications

The findings provide critical insights into the theoretical structure of knowledge production within the intersection of machine learning and EEG research. The observed concentration of influence among a small group of authors suggests an intellectual hierarchy that has driven foundational discourse but may also risk narrowing the scope of research perspectives. Over-reliance on a select group of contributors can lead to the perpetuation of dominant methodologies, potentially limiting the visibility of alternative or emerging theoretical approaches [42]. Theoretically, expanding contributions from underrepresented regions is essential not only for equity but for diversifying the mathematical and methodological frameworks utilized in the field. Furthermore, the disconnect between technical and clinical literature highlights a theoretical challenge: many advancements prioritize algorithmic refinements over practical constraints such as patient variability or interpretability [43]. Bridging this gap requires interdisciplinary frameworks that align algorithmic development with the requirements of real-world healthcare environments [44].

The heavy reliance on bibliometric metrics, such as the H-index, reflects a systemic limitation in academic evaluation. These metrics prioritize scholarly visibility but do not directly measure societal or clinical impact. For instance, a highly cited technical paper may achieve academic prominence without necessarily translating into clinical adoption if it fails to address usability or ethical concerns [45]. Theoretical evaluation systems should therefore evolve to integrate measures of translational success, such as usability in diverse settings. Additionally, incorporating ethical dimensions, including bias, data privacy, and transparency, into theoretical frameworks is crucial for ensuring that models are both equitable and effective [46, 47].

6.2. Practical Implications

This analysis highlights a significant scholarly need to align machine learning advancements with the practical requirements of clinical settings. Collaboration between technical experts and clinicians is essential to ensure that models are developed with usability and workflow integration in mind [48]. Current academic incentives often prioritize technical novelty over patient-centered impact; addressing this requires closer partnerships between engineers and medical professionals [41, 49]. Researchers in low- and middle-income countries (LMICs) face significant barriers to participation despite bearing a disproportionate share of the global epilepsy burden [50]. Addressing these disparities through equitable resource distribution and international partnerships can enrich the global research landscape with culturally sensitive and adaptable solutions [51, 52].

Diversifying the scientific community by supporting early-career researchers and underrepresented groups is essential for long-term innovation. Quality mentoring and the recognition of practical research can boost productivity and foster a more inclusive field [53, 54]. Ethical considerations, particularly addressing algorithmic bias and ensuring data privacy, should be central to research design [55, 56].

The underrepresentation of clinical research in the bibliometric data points toward a need for structural changes in funding and publication priorities [41, 57]. Journals and funding bodies can play a pivotal role by incentivizing interdisciplinary projects that demonstrate both technical rigor and clinical relevance [58, 59]. By fostering an inclusive and ethically grounded approach, the field can better ensure that technical innovations eventually translate into meaningful healthcare improvements for diverse global populations [60].

6.3. Limitations and Future Works

This study has several limitations inherent to bibliometric methodology. First, the analysis relies on citation data which, while effective for identifying academic trends, serves only as a proxy for scholarly influence and does not directly capture the practical implementation or clinical efficacy of research [61]. It is crucial to note that high citation counts for technical papers indicate academic attention but do not verify the reported algorithmic performance or the reproducibility of results in clinical settings. Future work could incorporate qualitative methods, such as expert interviews or systematic reviews, to contextualize these bibliometric findings within real-world healthcare practices.

A second limitation is the exclusive focus on Scopus-indexed journals, which may overlook valuable regional or grey literature, particularly from LMICs [62]. This exclusion, while ensuring data stability, potentially underrepresents local solutions to epilepsy management. Future analyses should expand the data corpus to include non-indexed regional journals to offer a more comprehensive view of global contributions.

The study does not provide an empirical examination of the structural factors, such as specific funding mandates or national AI policies, that influence the observed research output [63]. While correlations with country-level production were identified, future research should investigate these causal mechanisms through rigorous policy analysis. Furthermore, although the study highlights a disconnect between technical and clinical literature, the specific methods required to bridge this gap, such as joint training programs, necessitate further investigation [64].

Finally, there is a need for alternative evaluation metrics that go beyond citation counts to assess translational success [65, 66]. Tracking emerging keywords such as explainable AI (XAI) [67] and wearable EEG technologies [68] offers a pathway to monitor the field's shift toward usability. By addressing these limitations, future research can foster a more rigorous understanding of how machine learning advancements align with the needs of epilepsy diagnosis [60].

7. Conclusion

This study examined the research landscape of machine learning applications in EEG-based epileptic seizure diagnosis, focusing on influential works, research trends, and the contributions of key players. The findings offer a comprehensive view of how the field has progressed, the achievements made, and the challenges that remain. The first objective was to identify foundational articles that have shaped this research area. A small number of highly cited studies were found to drive significant methodological advancements and practical applications. While these works provide a strong foundation, their prominence also reflects a reliance on established approaches. Expanding the scope to include innovative methodologies could address persistent challenges and propel the field forward.

The second objective involved analysing research trends, including country-specific contributions. The findings reveal a steady growth in publications, with China and the United States leading in productivity and impact. However, the limited representation of low- and middle-income countries, despite their high epilepsy burden, highlights a persistent imbalance. Addressing this disparity by promoting inclusive participation can bring unique perspectives and context-sensitive solutions, enriching global research efforts.

The third objective assessed the influence of prominent authors and journals. Key contributors, such as Zhang Y and Wang Y, along with influential publications, including Biomedical Signal Processing and Control and Annals of Neurology, have been instrumental in advancing the field. While these contributions are significant, the concentration of influence within a limited group emphasizes the necessity of supporting emerging researchers and underrepresented regions. Diversifying scholarly input remains essential for fostering innovation and expanding the scope of research perspectives

Beyond these objectives, broader challenges were identified. Traditional bibliometric metrics, such as citation counts, provide limited insight into the practical relevance of research. Alternative evaluation methods that focus on clinical applicability, societal impact, and ethical considerations could offer a more comprehensive understanding of contributions. Additionally, ethical issues, including algorithmic bias, data privacy, and equitable access to technology, demand greater attention to ensure that advancements benefit diverse populations and healthcare systems. This study has achieved its goals by analysing the research landscape, identifying pivotal works, tracing trends, and evaluating the contributions of leading figures. While significant progress has been made, there is a pressing need to address gaps in diversity, collaboration, and the practical implementation of findings. By encouraging broader participation, fostering interdisciplinary collaborations, and focusing on real-world impact, the field can continue to evolve, ultimately improving epilepsy diagnosis and care for all.

Supplementary Information

Author Contributions. **Amirul Aizad Ahmad Fuad:** Conceptualization, Methodology, Validation, Formal Analysis, Investigation, Resources, Data Curation, Writing—Original Draft Preparation, Writing—Review and Editing, Visualization, Supervision, Project Administration, Funding Acquisition. **Ashraff Ruslan:** Conceptualization, methodology, software, validation, formal analysis, data curation, writing—review and editing, visualization.

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Conflict of interest. The authors declare no conflict of interest.

Data availability. The data used in this study were retrieved from the Scopus database. The specific search string used to generate the dataset is provided in Appendix I of the manuscript.

Abbreviations.

EEG	:	Electroencephalography
ML	:	Machine Learning
CNN	:	Convolutional Neural Networks
SVM	:	Support Vector Machines
ANN	:	Artificial Neural Networks
XAI	:	Explainable AI
LSTM	:	Long Short-Term Memory
RNN	:	Recurrent Neural Networks

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Appendix I

Field	Search String
Article title, Abstract, Keywords	("machine learning" OR "ML" OR "deep learning" OR "neural network*" OR "artificial neural network*" OR "ANN" OR "convolutional neural network*" OR "CNN" OR "recurrent neural network*" OR "RNN" OR "support vector machine*" OR "SVM" OR "random forest" OR "supervised learning" OR "unsupervised learning" OR "reinforcement learning" OR "classification algorithm*" OR "regression algorithm*" OR "predictive modelling" OR "pattern recognition" OR "computational learning" OR "feature extraction" OR "gradient boosting" OR "Bayesian networks" OR "fuzzy logic" OR "genetic algorithms" OR "transfer learning" OR "ensemble learning") AND ("electroencephalogram" OR "EEG" OR "electroencephalography" OR "EEG signal*" OR "EEG data" OR "EEG analysis" OR "EEG recording*" OR "EEG monitoring" OR "EEG patterns" OR "EEG frequency bands" OR "alpha waves" OR "beta waves" OR "delta waves" OR "theta waves" OR "gamma waves" OR "EEG signal processing" OR "EEG feature extraction" OR "EEG spectral analysis" OR "event-related potentials" OR "ERP" OR "quantitative EEG (qEEG)" OR "EEG source localization" OR "high-density EEG" OR "scalp EEG" OR "intracranial EEG" OR "EEG artifact removal" OR "EEG brain mapping") AND ("epileptic seizure*" OR "seizure detection" OR "seizure prediction" OR "ictal activity" OR "pre-ictal state" OR "post-ictal state" OR "convulsion*" OR "epileptic event*" OR "epileptic disorder*" OR "seizure monitoring" OR "focal seizure*" OR "generalized seizure*" OR "tonic-clonic seizure*" OR "absence seizure*" OR "myoclonic seizure*" OR "clonic seizure*" OR "tonic seizure*" OR "partial seizure*" OR "epileptiform activity" OR "epileptic syndrome*" OR "seizure frequency" OR "seizure threshold" OR "status epilepticus" OR "epileptic focus" OR "temporal lobe epilepsy" OR "drug-resistant epilepsy" OR "refractory epilepsy")