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Advancements and Applications of Machine Learning in Detecting Radon Nuclear Tracks from 2001 to 2023: A Bibliometric Analysis

Félix Díaz[1], Luis Sánchez[2], Rafael Liza[3], Jessica Toribio[4], Nhell Cerna[5]
[1]Vicerrectorado de Investigación, Universidad Autónoma del Perú, Perú, fediazdes@autonoma.edu.pe
[2]Universidad Privada del Norte, Perú, jusa295@gmail.com
[3]Universidad Tecnológica del Perú, Perú, c20231@utp.edu.pe
[4]Pontificia Universidad Católica del Perú, Perú, jessica.toribio@pucp.edu.pe
[5]Universidad Norbert Wiener, Perú, nhelldx@gmail.com

Abstract*– We present a bibliometric analysis of the advancements in machine learning for detecting radon nuclear tracks, using publications from 2001 to 2023 sourced from Scopus and Web of Science databases. We analyze the growth in research output, particularly highlighting contributions from China and the United States, and identify key themes such as "machine learning", "radon", "neural networks", and emerging methods like "xgboost" and "long short-term memory networks". Our findings underscore the collaborative efforts within the field, as evidenced by the global authorship networks. The research landscape is mapped out, revealing core and peripheral areas of study that define the current state and prospects of radon detection research. The present study encapsulates the evolution of the field and emphasizes the necessity for continued interdisciplinary collaboration to enhance radon risk assessment methods.

Keywords-- Machine Learning, Nuclear Tracks, Bibliometric.

I. Introduction

The significance of radon detection, a radioactive gas classified by the International Agency for Research on Cancer (IARC) as a Class 1 carcinogen [1], lies in its ability to accumulate in enclosed spaces, emanating from geological and construction materials, and its direct association with increased lung cancer risk following prolonged exposures to high concentrations [2-13]. This public health challenge has driven the evolution of advanced techniques for effective radon detection, becoming a crucial area of interest in environmental and residential research [14-21]. Since the early 20th century, radon detection has been a cornerstone in advancing nuclear physics and radioactivity, with traditional methods ranging from nuclear emulsion photography to solid trace detectors, albeit limited by the need for development and manual analysis [21-43].

In parallel, machine learning, rooted in computer science and statistics since the 1950s, has undergone a significant transformation, particularly with the technological renaissance of the 21st century characterized by increased data availability and computing capacity [44-52]. This progress has been particularly notable in developing deep learning algorithms and neural networks, facilitating advances in natural language processing, computer vision, and the detection and analysis of radiological phenomena [53-61]. Applying these technologies to study nuclear traces has revolutionized previous methodologies, allowing for more efficient and accurate analysis and new directions for research in environmental health and public safety [62-65].

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In this context, bibliometric analysis is an essential strategic tool for evaluating research trends and identifying existing knowledge gaps through concrete indicators such as citations, publications, and keywords [66-70]. Despite advancements in radon detection and machine learning, the literature needs a comprehensive bibliometric analysis that merges both fields from a global perspective. While independent systematic and bibliometric reviews exist in each area [71-79], the intersection of these disciplines and their joint application in radon detection has yet to be explored exhaustively.

Therefore, this study aims to fill this gap, employing recognized databases such as Scopus and Web of Science to conduct a detailed bibliometric analysis that not only maps the temporal distribution of publications and identifies the most productive authors but also highlights significant contributions from countries and institutions, and reveals the predominant terminology in this emerging interdisciplinary field. This approach will illuminate the current state of research and guide future directions in this burgeoning multidisciplinary field.

II. Methodology

This investigation employs bibliometric methodologies to systematically scrutinize and evaluate the extant literature on artificial intelligence and environmental contamination by radon. Through statistical techniques, our bibliometric analysis assesses the scientific contributions and impact of publications across various research domains. We sourced documents from renowned bibliographic databases such as SCOPUS and Web of Science, analyzing and depicting them through graphical representations to elucidate the intellectual and conceptual development within the field. The latter was achieved by examining aspects such as citations, keywords, and authorships [80]. Metrics such as citations per article, author, and/or the country of the institution have been employed to ascertain the influence of the published literature on research and to gauge the specific contributions and impact of authors, journals, and institutions within each research domain [81-83].

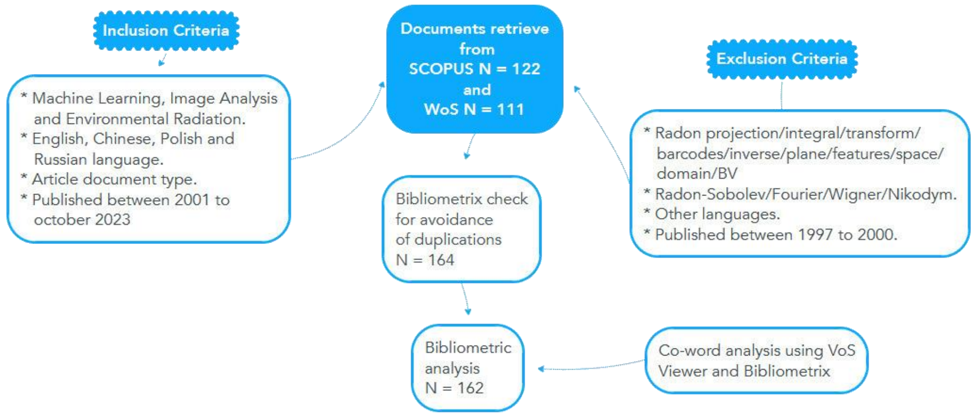

Figure 1: Search Process Flowchart for the Bibliometric Review.

In light of the significant scientific and technological advancements in the 21st century, particularly in the field of Machine Learning, our focus has been narrowed to publications from 2001 to 2023 [66]. This period was selected for its statistical significance and encompassing the most contemporary and pertinent trends within the field.

Exclusion criteria were applied to terms including "*Radon Projection*", "*Radon Integral*", "*Radon Transform*", "*Radon Barcodes*", "*Radon Inverse*", "*Radon-Sobolev*", "*Radon Plane*", and "*Radon Features*", as delineated in Figure 1 and Table 1. This approach was adopted to omit the works attributed to Johann Radon in mathematics and its applications. Furthermore, the analysis was confined solely to articles, excluding conference papers, book chapters, and books.

Figure 1 illustrates the research design of this study, employing a search strategy in SCOPUS and Web of Science (WoS) that incorporated the keywords listed in Table 1. A search encompassing titles, abstracts, and keywords (TS) was utilized to identify pertinent articles. This search yielded 233 articles published in journals indexed by Scopus and Web of Science. The relevance of each article was manually verified, leading to the exclusion of 69 duplicate articles, resulting in a total of 164 articles for the bibliometric analysis.
The study was conducted in two principal stages: the initial stage involved identifying contributions from the Scopus and Web of Science (WoS) databases, and the subsequent stage entailed conducting a bibliometric analysis using the bibliometric package in RStudio and VOSviewer version 1.6.20.

Table 1: Search Strategy Components for Bibliometric Analysis.

Component	**Description**	**Terms / Operators**
Keywords Group 1	Terms relates to AI Technologies	"Machine Learning", "Deep Learning", "Neural Network", "Artificial Neural Network", "Deep Neural Network", "Artificial Intelligence", "Convolutional Neural Network", "Automated learning", "Computational intelligence", "Neural network modeling", "Cognitive computing", "Machine Intelligence", "Neural models", "Neural computing", "Neural systems", "Perceptron models", "Data mining"
Keywords Group 2	Terms relates to Radon Detection	"nuclear tracks", "CR39", "CR-39", "Radon", "LR115", "LR-115", "SSNTD", "Makrofol", "Lexan", "NTA film", "nitrocellulose triacetate", "Track detector"
Excluded Keywords	Terms to Excluded	"Radon projection", "Radon transformation", "Radon integral", "Radon transform", "Radon transformed", "Radon Barcodes", "Radon Cumulative Distribution", "Radon BV", "Radon inversion", "Inverse Radon", "Radon Inverse", "Radon-Fourier transform", "Radon-Wigner transform", "Radon space", "Radon domain", "Radon-Sobolev", "Radon plane", "Radon Features", "Radon-Nikodym", "Radon scale transformation"
Boolean Operators	Connectors for combining terms	OR (within each group), AND (between groups), AND NOT (to exclude terms)
Search Fields	Specific areas of the database	Title, Abstract, Keywords (TITLE-ABS-KEY)
Filters	Criteria for refining the search	Document Type: Article (LIMIT-TO (DOCTYPE, "ar"))

III. ANALYSIS AND DISCUSSION

A. *Countries with the highest scientific production.*

Figure 2 presents a bar chart illustrating the distribution of scientific publications by corresponding authors' countries, differentiated by single-country publications (SCP) and multiple-country publications (MCP), indicative of international collaborations. From Figure 2, China leads significantly in the number of documents published, with a substantial number of SCPs and a smaller yet notable amount of MCPs. This suggests a robust domestic research output in China and active international collaboration. The United States follows, displaying a balanced proportion of SCPs and MCPs, indicating robust national and international research activities. South Korea, India, and Italy also show considerable scientific output, with South Korea and Italy having more SCPs than MCPs. In contrast, India shows a more balanced distribution between SCPs and MCPs. The latter could reflect differing research practices or the nature of international partnerships within these countries. Turkey, Iran, and Nigeria have a relatively higher number of MCPs than SCPs, implying that researchers in these countries may be more engaged in international collaborations. The aforementioned could be due to various factors, including the global nature of certain research topics or the pursuit of expertise and resources from multiple countries. Countries such as Serbia, Slovenia, and Germany show a mix of SCPs and MCPs, with Germany having a higher count of MCPs, underscoring its international solid collaborative links. Japan, Ireland, and Poland present a modest number of publications, with Japan having a slightly higher inclination towards SCPs. Meanwhile, Vietnam, Australia, Finland, and Jordan contribute a smaller number of documents, with a trend towards MCPs for Vietnam and Finland, suggesting these countries may actively seek international research collaborations. Figure 2 demonstrates the varying degrees of scientific production and collaborative tendencies among countries in machine learning applications for radon detection. The distribution of SCPs and MCPs provides insight into the collaborative dynamics and research capacity of different nations within this scientific arena.

The data visualized in Figure 3 indicates that certain regions demonstrate a higher concentration of research output, particularly in North America, East Asia, and parts of Europe. The United States and China, discernible by their darker hues, are leading in the number of contributions that reflect robust national research infrastructures and investment in the scientific study of machine learning and radon detection. European countries also display substantial scientific production, suggesting active research communities and funding mechanisms supporting such endeavors. Conversely, countries represented by lighter shades, encompassing much of Africa, Central Asia, and other parts of South America, exhibit lower levels of scientific output. This distribution may underscore the variations in resource allocation, research prioritization, or the availability of advanced technological infrastructure necessary for conducting high-level research in machine learning applications for radon detection.

Moreover, the map (Figure 3) indicates a substantial scope for international collaboration. Nations with a pronounced level of scientific output could play a pivotal role in fostering research partnerships, potentially aiding in advancing the field through shared knowledge and resources. Conversely, regions with less intensive research activity might benefit from such collaborative efforts, enhancing their scientific contribution and integration into the global research community.

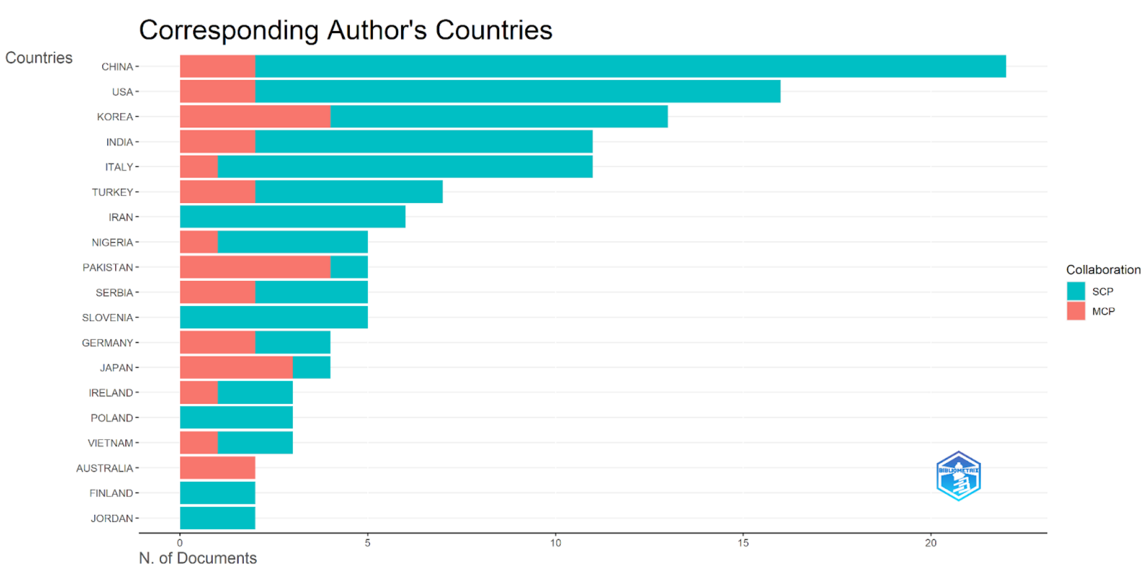

Figure 2: Distribution of Scientific Publications by Country

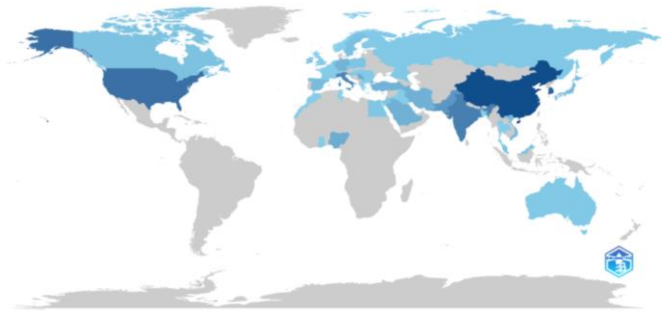

Figure 3: Country Scientific Production.

B. Most frequent keywords.

Figure 4 offers a network visualization map, a graphical abstraction of the thematic terrain derived from the literature analyzed. This figure illuminates the principal findings through the interconnected nodes and linkages depicted in the visualization, shedding light on the principal themes, subsidiary themes, and the overarching developmental trajectory within the specified timeframe. Among the key findings is the dominant theme of “machine learning”, which appears as the most salient node within the network map. Contiguous to this is the node labeled “radon”, highlighting its significant exploration within the ambit of machine learning advancements. Branching from the “machine learning” epicenter are various subsidiary themes and associated concepts, such as “deep learning”, “neural networks”, and “anomaly detection”. The nearness and magnitude of these nodes relative to “machine learning” reflect their import and recurrent employment in radon detection scenarios. “Neural networks”, in particular, are a focal subtheme, indicating a specialized technological avenue within the broader machine learning schema. The interdisciplinary character of the research is accentuated by nodes associated with terms like "indoor air quality" and "earthquake prediction". These nodes represent the application of machine learning across heterogeneous domains, demonstrating the versatility of machine learning methodologies in tackling assorted environmental and geophysical challenges. Emerging terms such as "xgboost", "lstms" (long short-term memory networks), and "anomaly detection" signal an escalating interest in advanced machine learning techniques. "Xgboost" represents a robust implementation of gradient boosting machines, heralding a shift toward more formidable predictive models in radon detection. The occurrence of "lstms" on the map denotes a burgeoning interest in employing these networks to process and forecast temporal data, which is highly germane to environmental monitoring of radon.

Furthermore, "anomaly detection" centers on pinpointing deviations or atypical patterns in radon levels, potentially imperative for early warning systems in radon contamination and exposure scenarios, see Figure 4. The latter aligns with a proactive stance in environmental health and safety, leveraging machine learning to comprehend and foresee potential hazards. Additionally, geographical nuances are discernible by including nodes such as “Ohio” and “South Korea”. The presence of these terms within the map intimates localized research endeavors or substantial contributions from these regions, potentially shaping the direction or focus of the field. These geographical references among emerging terms suggest region-specific research, pointing to unique radon-related challenges encountered in distinct locales or the evolution of specialized machine learning applications tailored to local or regional exigencies.

Figure 4 also shows that the network map further features a temporal color gradient, indicating the evolution of research emphasis over time. Although the precise temporal delineation for each color is unspecified, the color spectrum represents shifts in research concentration from 2001 to 2023. This visual element narrates the progression of the field, the possible advent of novel trends, or the waning of previous focal points. The robustness of the links within the network denotes the co-occurrence strength between thematic terms. Thicker lines suggest terms frequently appearing in tandem, highlighting well-established connections in the body of research, especially between “deep learning” and “neural networks”. These strong associations suggest a cohesive research dialogue within the domain.

C. Authors and their collaborative networks.

Figure 5 visually represents the scholarly networks within the research community. This authorship network map elucidates the collaborative landscape and publication output among scholars in this domain. The figure shows varying-sized nodes representing individual researchers and their scientific contributions. Larger nodes, such as those associated with 'Kumar, Ashok' and 'Chua, Kuang,' suggest that these authors have a considerable influence in the field through more publications or their central roles in collaborative research networks. Their prominence on the map indicates a strong presence within the literature concerned with machine learning in radon detection.

The density and thickness of the lines that connect these nodes provide insight into the strength and frequency of collaborative ties between researchers. A densely interconnected cluster around “Kumar, Ashok” indicates a robust collaborative network, suggesting this author's pivotal role in fostering collaborative research efforts. Distinct clusters identified within the network map reveal groups of authors who frequently co-author papers or share thematic research interests. Such clusters, as seen with authors like “Chua, Kuang” and “Acharya, U. Rajendra”, imply a close-knit research community with shared methodologies or converging on similar topics within the expansive machine learning and radon detection field.

Figure 4 also introduces a temporal dimension in the visualization through a color gradient applied to the nodes, representing the authors' periods of activity from 2001 to 2023. Nodes colored in cooler hues, such as “Ng, E.Y.K.”, reflect activity earlier in the timeline. Meanwhile, those in warmer tones, like “Lee, Saro”, represent authors whose research contributions have been more recent.

D. Thematic Map.

Figure 6 shows a strategic diagram that categorizes various research themes based on their centrality to the field and the extent of their development. This analytical framework facilitates the identification of mature, emerging, and foundational areas within machine learning and radon detection. The diagram is divided into four quadrants, each representing a different typology of research themes. The vertical axis measures the density or developmental degree of themes, indicating the depth of research and the interconnectedness of studies within each theme. The horizontal axis assesses centrality, reflecting the prominence and influence of themes within the broader research network. Niche themes, positioned in the upper left quadrant, such as “explainable artificial intelligence”, “convolutional neural network”, and 'indoor air pollution,' exhibit a high level of development. Despite their dense research activity, these themes are less central to the broader discourse, suggesting they are highly specialized areas that may appeal to particular segments within the research community. Conversely, motor themes in the upper right quadrant, including “earthquake prediction” “earthquakes” and “neural networks”, represent well-developed and central research areas. These themes are pivotal, often propelling the field's progression and signaling areas of substantial scholarly engagement and cross-disciplinary relevance. Fundamental to the field are basic themes, such as “radon”, “machine learning” and “artificial neural network” located in the lower right quadrant. Despite their foundational role and high centrality, these areas have yet to reach the same level of thematic development as motor themes, suggesting potential for further exploration and expansion. Emerging or declining themes reside in the lower left quadrant. Here, themes like “groundwater”, “prediction”, and “indoor radon” are characterized by lower centrality and development. These represent nascent areas ripe for growth or domains witnessing a reduction in focus within the current research landscape.

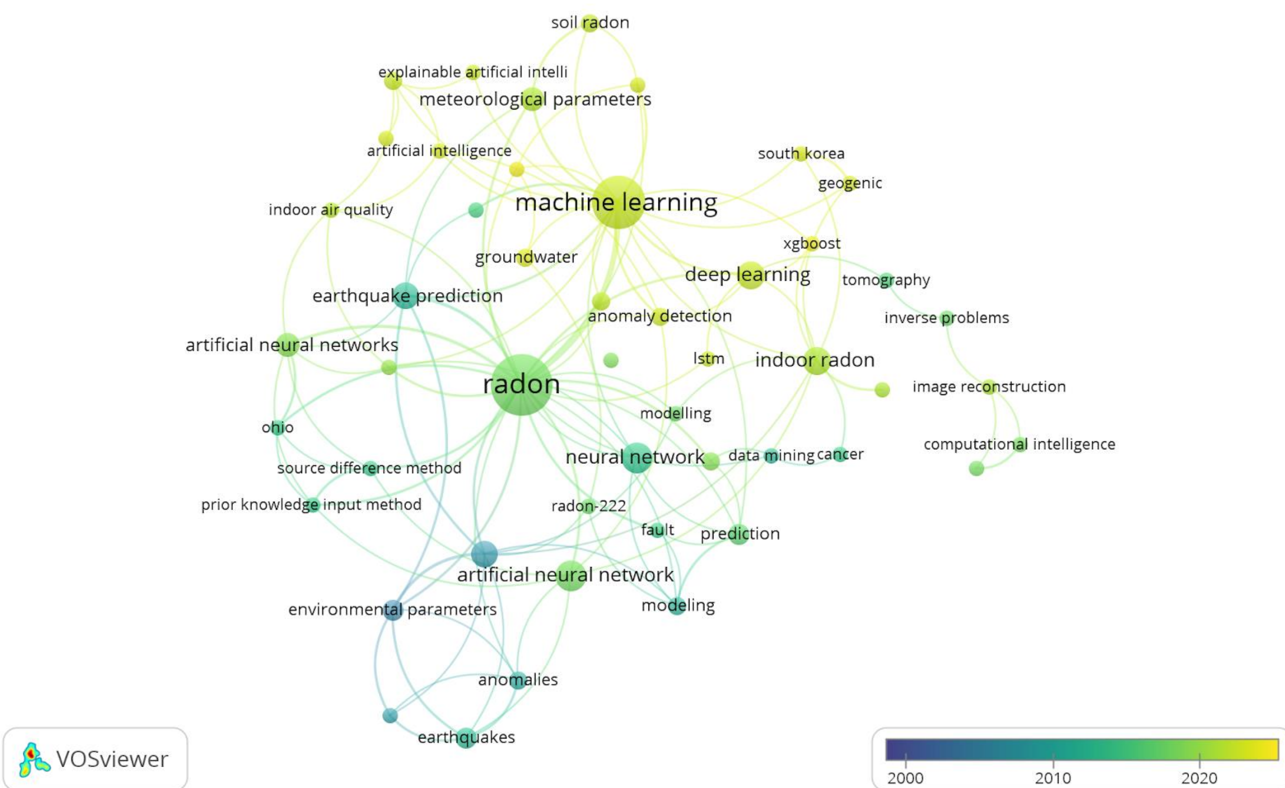

Figure 4: Thematic Network Visualization of Keywords.

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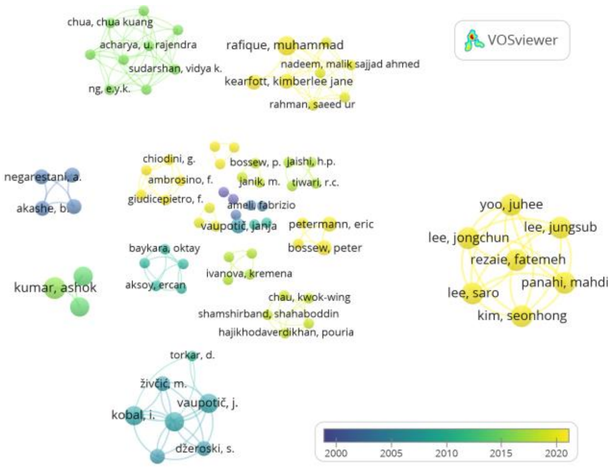

Figure 5: Map of authors with the greatest scientific production and their collaborative networks.

IV. CONCLUSIONS

The bibliometric analysis of the advancements and applications of machine learning in detecting radon nuclear tracks has demonstrated a significant international effort in scientific production. China and the United States have emerged as leaders in the field, exhibiting a robust output of research domestically and through international collaborations—the balanced mix of single-country and multiple-country publications further evidence this global effort.

Analysis of the research output by country has revealed a geographical distribution of scientific production and varying degrees of collaboration tendencies. Nations with substantial scientific output, such as Germany, have shown solid international collaborative links, while others, including Vietnam and Finland, are actively seeking international research partnerships.

Examining the most frequent keywords and themes has illuminated "machine learning", "radon", "neural networks", "deep learning", and "anomaly detection" as central to the literature. These keywords encapsulate the core of the field focus areas and the integration of advanced computational techniques in radon detection, with emerging terms suggesting a continued evolution toward sophisticated analytical models.

The study of authors and collaborative networks has highlighted influential researchers and the importance of scholarly communication in advancing the field. It has revealed a landscape characterized by varied node sizes, representing the extent of individual authors' contributions and their centrality within the collaborative network.

The strategic thematic map categorizes research themes into well-established, emerging, and specialized areas. Basic themes like "radon", "machine learning", and "artificial neural networks" have high centrality but varied development, indicating areas ripe for further exploration.

Finally, we conclude that the field of machine learning for radon detection is marked by dynamic research activity, innovative methodological approaches, and a strong trend toward international collaboration. The findings are a foundation for guiding future research directions and fostering an inclusive global research community in this critical public health and environmental safety area.

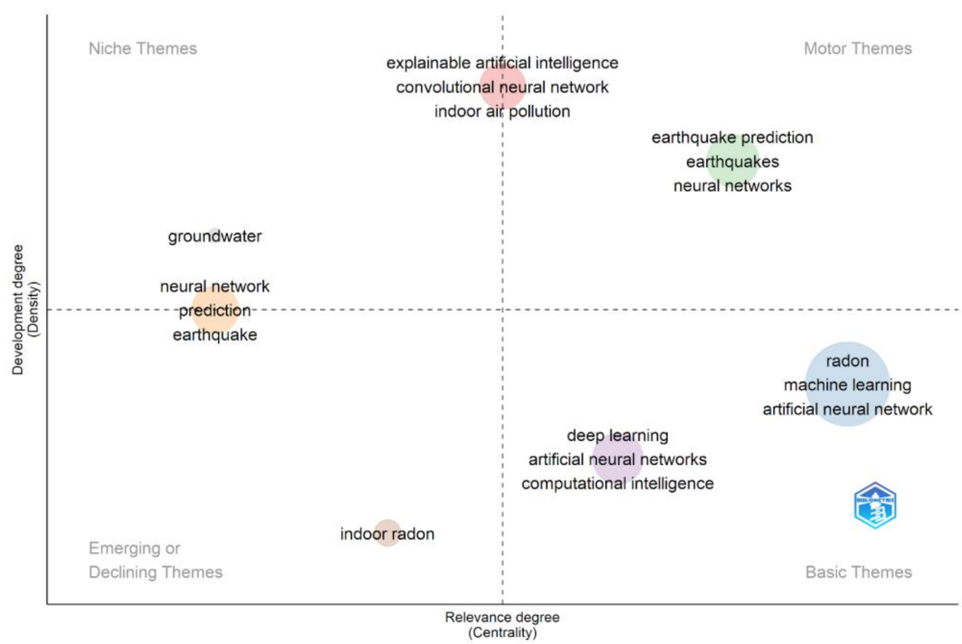

Figure 6: Strategic Diagram of Research Themes.

REFERENCES

[1] International Agency for Research on Cancer (IARC), ICRP PUBLICATION 126. SAGE Publications Limited, 2014. Available: https://publications.iarc.fr/Book-And-Report-Series/Iarc-Monographs-On-The-Identification-Of-Carcinogenic-Hazards-To-Humans/Man-Made-Mineral-Fibres-And-Radon-1988

[2] L. Vimercati et al., "Radon Levels in Indoor Environments of the University Hospital in Bari-Apulia Region Southern Italy," International Journal of Environmental Research and Public Health, vol. 15, no. 4, pp. 694–694, Apr. 2018, doi: https://doi.org/10.3390/ijerph15040694.

[3] P. Gopalakrishnan and J. Jeyanthi, "Importance of radon assessment in indoor Environment-a review," Materials Today: Proceedings, vol. 56, pp. 1495–1500, Jan. 2022, doi: https://doi.org/10.1016/j.matpr.2021.12.534.

[4] D. Bodansky, R. M. A, and S. D. R, "Indoor radon and its hazards," Osti.gov, 1987. https://www.osti.gov/biblio/6470069 (accessed Jan. 30, 2024).

[5] J. D. Appleton and J. C. H. Miles, "A statistical evaluation of the geogenic controls on indoor radon concentrations and radon risk," Journal of Environmental Radioactivity, vol. 101, no. 10, pp. 799–803, Oct. 2010, doi: https://doi.org/10.1016/j.jenvrad.2009.06.002.

[6] Gunby, J. A. et al. "Factors Affecting Indoor Radon Concentrations in the United ...: Health Physics," LWW, 2024. https://journals.lww.com/health-physics/Abstract/1993/01000/Factors_Affecting_Indoor_Radon_Concentrations_in.1.aspx (accessed Jan. 30, 2024).

[7] Ji Young Yoon, Jung Dong Lee, So Won Joo, and Dae Ryong Kang, "Indoor radon exposure and lung cancer: a review of ecological studies," Annals of occupational and environmental medicine, vol. 28, no. 1, Mar. 2016, doi: https://doi.org/10.1186/s40557-016-0098-z.

[8] Goran Pershagen et al., "Residential Radon Exposure and Lung Cancer in Sweden," The New England Journal of Medicine, vol. 330, no. 3, pp. 159–164, Jan. 1994, doi: https://doi.org/10.1056/nejm199401203300302.

[9] Neuberger, John S.; Gesell, Thomas F.. RESIDENTIAL RADON EXPOSURE AND LUNG CANCER: RISK IN NONSMOKERS. Health Physics 83(1):p 1-18, July 2002, https://journals.lww.com/health-physics/toc/2002/07000 (accessed Jan. 31, 2024)

[10] R. William. Field et al., "The Iowa radon lung cancer study — phase I: residential radon gas exposure and lung cancer," Science of The Total Environment, vol. 272, no. 1–3, pp. 67–72, May 2001, doi: https://doi.org/10.1016/s0048-9697(01)00666-0.

[11] Michael, R. C. Brownson, J. H. Lubin, E. Berger, J. Chang, and J. D. Boice, "Residential Radon Exposure and Lung Cancer Among Nonsmoking Women," PubMed, vol. 86, no. 24, pp. 1829–1837, Dec. 1994, doi: https://doi.org/10.1093/jnci/86.24.1829.

[12] Pavia, "Meta-analysis of residential exposure to radon gas and lung cancer," Bulletin of the World Health Organization, vol. 81, no. 10, 2022, Accessed: Jan. 31, 2024. [Online]. Available: https://pubmed.ncbi.nlm.nih.gov/14758433/

[13] J. M. Samet, "Radon and Lung Cancer," PubMed, vol. 81, no. 10, pp. 745–758, May 1989, doi: https://doi.org/10.1093/jnci/81.10.745.

[14] J. C. H. Miles and E. J. Dew, "A PASSIVE RADON GAS DETECTOR FOR USE IN HOMES," Elsevier eBooks, pp. 569–572, Jan. 1982, doi: https://doi.org/10.1016/b978-0-08-026509-4.50121-5.

[15] Jamshid Soltani-Nabipour, Abdollah Khorshidi, and F. Sadeghi, "Constructing Environmental Radon Gas Detector and Measuring Concentration in Residential Buildings," Physics of Particles and Nuclei Letters, vol. 16, no. 6, pp. 789–795, Nov. 2019, doi: https://doi.org/10.1134/s154747711906030x.

[16] Y. Rodal, A. Shemer, A. Schwarz, Nisan Ozana, Hovav Zafrir, and Zeev Zalevsky, "Usage of fiber optics as an underground deployable radon gas detector," OSA continuum, vol. 4, no. 12, pp. 3026–3026, Nov. 2021, doi: https://doi.org/10.1364/osac.444262.

[17] A. Miles, R. H. Griffin, Y. Shen and N. G. Tarr, "A wireless solution for radon gas detection," 2009 2nd Microsystems and Nanoelectronics Research Conference, Ottawa, ON, Canada, 2009, pp. 88-91, doi: 10.1109/MNRC15848.2009.5338954.

[18] Rahim Arsia, Mohammad Kazem Salem, A. Negarestani, and Amir Hossein Sari, "A new approach to measure radon by Thick Gas Electron Multiplier," Radiation Physics and Chemistry, vol. 196, pp. 110114–110114, Jul. 2022, doi: https://doi.org/10.1016/j.radphyschem.2022.110114.

[19] C. Papastefanou, "Measuring radon in soil gas and groundwaters: a review," Earth-prints.org, 2024, doi: http://hdl.handle.net/2122/3870.

[20] Ayman mohamed Abdalla, "CPRD Supplied With Native Scintillator for Radon Gas Detection," Arab Journal of Nuclear Sciences and Applications (Print), vol. 52, no. 3, pp. 90–97, Jul. 2019, doi: https://doi.org/10.21608/ajnsa.2019.5723.1130.

[21] L. Tommasino, "Radon monitoring by alpha track detection," International Journal of Radiation Applications and Instrumentation. Part D. Nuclear Tracks and Radiation Measurements, vol. 17, no. 1, pp. 43–48, Jan. 1990, doi: https://doi.org/10.1016/1359-0189(90)90147-p.

[22] S. A. Durrani, "Nuclear tracks: A success story of the 20th century," Radiation Measurements, vol. 34, no. 1–6, pp. 5–13, Jun. 2001, doi: https://doi.org/10.1016/s1350-4487(01)00112-3.

[23] R. Ilić, T. Šutej, J. Skvarč, and M. Humar, "Current research on nuclear tracks in solids at J. Stefan Institute," Nuclear Tracks and Radiation Measurements, vol. 21, no. 3, pp. 397–403, Jul. 1993, doi: https://doi.org/10.1016/0969-8078(93)90237-x.

[24] N. Du, L. Liao, Y. Xiao, X. Xiao, Z. Zhao, and Y. Lin, "Determination of radon using solid state nuclear tracks wireless sensing method," Analytica Chimica Acta, vol. 686, no. 1–2, pp. 121–125, Feb. 2011, doi: https://doi.org/10.1016/j.aca.2010.11.044.

[25] F. A. Abu-Jarad, "Application of nuclear track detectors for radon related measurements," International Journal of Radiation Applications and Instrumentation. Part D. Nuclear Tracks and Radiation Measurements, vol. 15, no. 1–4, pp. 525–534, Jan. 1988, doi: https://doi.org/10.1016/1359-0189(88)90195-1.

[26] D. Mazur, M. Janik, J. Łoskiewicz, P. Olko, and J. Swakoń, "Measurements of radon concentration in soil gas by CR-39 detectors," Radiation Measurements, vol. 31, no. 1–6, pp. 295–300, Jun. 1999, doi: https://doi.org/10.1016/s1350-4487(99)00135-3.

[27] Murtadha Sh. Aswood, M. S. Jaafar, and Sabar Bauk, "Measuring Radon Concentration Levels in Fertilizers Using CR-39 Detector," Advanced Materials Research, vol. 925, pp. 610–613, Apr. 2014, doi: https://doi.org/10.4028/www.scientific.net/amr.925.610.

[28] B. A. Almayahi, A. A. Tajuddin, and M. S. Jaafar, "Calibration technique for a CR-39 detector for soil and water radon exhalation rate measurements," Journal of Radioanalytical and Nuclear Chemistry, vol. 301, no. 1, pp. 133–140, Apr. 2014, doi: https://doi.org/10.1007/s10967-014-3146-6.

[29] Dragoslav Nikezić, "Determination of detection efficiency for radon and radon daughters with CR 39 track detector — a Monte Carlo study," vol. 344, no. 2, pp. 406–414, May 1994, doi: https://doi.org/10.1016/0168-9002(94)90090-6.

[30] A. J. Khan, A. K. Varshney, R. Prasad, R. K. Tyagi, and T. V. Ramachandran, "Calibration of a CR-39 plastic track detector for the measurement of radon and its daughters in dwellings," International Journal of Radiation Applications and Instrumentation. Part D. Nuclear Tracks and Radiation Measurements, vol. 17, no. 4, pp. 497–502, Jan. 1990, doi: https://doi.org/10.1016/1359-0189(90)90008-l.

[31] Y. M. Abbas, T. M. Hegazy, M. S. Nassif, M. Y. Shoeib, and A. F. Abd-Elraheem, "Measurement of 226Ra concentration and radon exhalation rate in rock samples from Al-Qusair area using CR-39," Journal of Radiation Research and Applied Sciences, vol. 13, no. 1, pp. 102–110, Jan. 2020, doi: https://doi.org/10.1080/16878507.2019.1706264.

[32] S. Bing, "CR-39 radon detector," Nuclear Tracks and Radiation Measurements, vol. 22, no. 1–4, pp. 451–454, Jan. 1993, doi: https://doi.org/10.1016/0969-8078(93)90106-e.

[33] N. F. Salih, "Determine the Contaminations of Radon in the Drinking Water Using NTDs (CR-39) and RAD7 Detectors," Arabian Journal for Science and Engineering, vol. 46, no. 6, pp. 6061–6074, Jan. 2021, doi: https://doi.org/10.1007/s13369-020-05267-y.

[34] M. Calamosca, S. Penzo, and G. Gualdrini, "The features of the new radon gas CR-39 dosemeter developed at the ENEA Institute of Radioprotection," Radiation Measurements, vol. 36, no. 1–6, pp. 221–224, Jun. 2003, doi: https://doi.org/10.1016/s1350-4487(03)00127-6.

[35] L. A. Najam, N. F. Tawfiq, and Rana Hesham Mahmood, "Radon Concentration in Some Building Materials in Using CR-39 Track

Detector," The International Journal of Physics, vol. 1, no. 3, pp. 73–76, Jan. 2013, doi: https://doi.org/10.12691/ijp-1-3-3.
[36]B. Pérez, M.E. López, and D. Palacios, "Concentric rings formation on etched LR-115 in bare mode by unconventional exposition," vol. 496, pp. 37–44, Jun. 2021, doi: https://doi.org/10.1016/j.nimb.2021.03.014.
[37]B. Pérez, M.E. López, and D. Palacios, "Theoretical and experimental study of the LR-115 detector response in a non-commercial radon monitor," Applied Radiation and Isotopes, Jun. 2020, doi: https://doi.org/10.1016/j.apradiso.2020.109112.
[38]F. De Cicco, M. Pugliese, V. Roca, and C. Sabbarese, "Track counting and thickness measurement of LR115 radon detectors using a commercial image scanner," Radiation Protection Dosimetry, vol. 162, no. 3, pp. 388–393, Dec. 2013, doi: https://doi.org/10.1093/rpd/nct310.
[39]H. A. S, "Radon concentrations in some Egyptian dwellings using LR 115 detectors," Osti.gov, Jun. 15, 2007. https://www.osti.gov/etdeweb/biblio/20935465 (accessed Jan. 31, 2024).
[40]F. De Cicco, M. Pugliese, V. Roca, and C. Sabbarese, "Dependence of the LR-115 radon detector calibration factor on track density," Applied Radiation and Isotopes, vol. 78, pp. 108–112, Aug. 2013, doi: https://doi.org/10.1016/j.apradiso.2013.03.028.
[41]D. Nikezic and K. N. Yu, "Long-term determination of airborne concentrations of unattached and attached radon progeny using stacked LR 115 detector with multi-step etching," Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment, vol. 613, no. 2, pp. 245–250, Feb. 2010, doi: https://doi.org/10.1016/j.nima.2009.11.058.
[42]J. Kvasnicka, Vladimir Zdimal, and A. Seini, "Monitoring of the unattached fraction of radon progeny by the Kodak LR-115 Type 2, nuclear track detector," vol. 1000, pp. 165248–165248, Jun. 2021, doi: https://doi.org/10.1016/j.nima.2021.165248.
[43]Essam Mohammed Rasheed, "Determination the Concentration of the Radon in some Drinking Bottled Water in Baghdad using LR-115 Detector," Baghdad Science Journal, vol. 9, no. 4, 2023, Accessed: Jan. 31, 2024. [Online]. Available: https://iasj.net/iasj/article/63355
[44]SAMUEL, Arthur L. Some studies in machine learning using the game of checkers. IBM Journal of research and development, 1959, vol. 3, no 3, p. 210-229.
[45]SAMUEL, Arthur L. Machine learning. The Technology Review, 1959, vol. 62, no 1, p. 42-45.
[46]MITCHELL, Tom Michael. The discipline of machine learning. Pittsburgh: Carnegie Mellon University, School of Computer Science, Machine Learning Department, 2006.
[47] C. Chu et al., "Map-Reduce for Machine Learning on Multicore," Advances in Neural Information Processing Systems, vol. 19, 2024, Accessed: Jan. 31, 2024. [Online]. Available: https://proceedings.neurips.cc/paper/2006/hash/77ee3bc58ce560b86c2b59363281e914-Abstract.html
[48]M. I. Jordan, T. M. Mitchell ,Machine learning: Trends, perspectives, and prospects.Science349,255-260(2015).DOI:10.1126/science.aaa8415
[49]O. Y. Al-Jarrah, P. D. Yoo, Sami Muhaidat, G. K. Karagiannidis, and K. Taha, "Efficient Machine Learning for Big Data: A Review," Big Data Research, vol. 2, no. 3, pp. 87–93, Sep. 2015, doi: https://doi.org/10.1016/j.bdr.2015.04.001.
[50]L. Zhou, S. Pan, J. Wang, and A. V. Vasilakos, "Machine learning on big data: Opportunities and challenges," Neurocomputing, vol. 237, pp. 350–361, May 2017, doi: https://doi.org/10.1016/j.neucom.2017.01.026.
[51]G. Carleo et al., "Machine learning and the physical sciences," Reviews of Modern Physics, vol. 91, no. 4, Dec. 2019, doi: https://doi.org/10.1103/revmodphys.91.045002.
[52]A. Singh, N. Thakur and A. Sharma, "A review of supervised machine learning algorithms," 2016 3rd International Conference on Computing for Sustainable Global Development (INDIACom), New Delhi, India, 2016, pp. 1310-1315.
[53]Abdullah Ayub Khan, Asif Ali Laghari, and Shafique Ahmed Awan, "Machine Learning in Computer Vision: A Review," ICST Transactions on Scalable Information Systems, pp. 169418–169418, Jul. 2018, doi: https://doi.org/10.4108/eai.21-4-2021.169418.
[54]Athanasios Voulodimos, Nikolaos Doulamis, and Eftychios Protopapadakis, "Deep Learning for Computer Vision: A Brief Review," Computational Intelligence and Neuroscience, vol. 2018, pp. 1–13, Jan. 2018, doi: https://doi.org/10.1155/2018/7068349.
[55]V. Wiley and T. Lucas, "Computer Vision and Image Processing: A Paper Review," International journal of artificial intelligence research, vol. 2, no. 1, pp. 22–22, Jun. 2018, doi: https://doi.org/10.29099/ijair.v2i1.42.
[56]A. Resler, Reuven Yeshurun, Filipe Natalio, and Raja Giryes, "A deep-learning model for predictive archaeology and archaeological community detection," Humanities and Social Sciences Communications, vol. 8, no. 1, Nov. 2021, doi: https://doi.org/10.1057/s41599-021-00970-z.
[57]J. Zhang et al., "Computer vision and machine learning for robust phenotyping in genome-wide studies," Scientific Reports, vol. 7, no. 1, Mar. 2017, doi: https://doi.org/10.1038/srep44048.
[58]P. J. Navarro, F. Pérez, J. Weiss, and M. Egea-Cortines, "Machine Learning and Computer Vision System for Phenotype Data Acquisition and Analysis in Plants," Sensors, vol. 16, no. 5, pp. 641–641, May 2016, doi: https://doi.org/10.3390/s16050641.
[59]S. Wang and R. M. Summers, "Machine learning and radiology," Medical Image Analysis, vol. 16, no. 5, pp. 933–951, Jul. 2012, doi: https://doi.org/10.1016/j.media.2012.02.005.
[60]A. Esteva et al., "Deep learning-enabled medical computer vision," npj Digital Medicine, vol. 4, no. 1, Jan. 2021, doi: https://doi.org/10.1038/s41746-020-00376-2.
[61]Z. Zhang and E. Sejdić, "Radiological images and machine learning: Trends, perspectives, and prospects," Computers in Biology and Medicine, vol. 108, pp. 354–370, May 2019, doi: https://doi.org/10.1016/j.compbiomed.2019.02.017.
[62]D. Valcarce, A. Alvarellos, Juan Ramón Rabuñal, J. Dorado, and M. Gestal, "Machine Learning-Based Radon Monitoring System," Chemosensors, vol. 10, no. 7, pp. 239–239, Jun. 2022, doi: https://doi.org/10.3390/chemosensors10070239.
[63]Hari Prasad Jaishi, S. Singh, Raghavendra Prasad Tiwari, and Ramesh Chandra Tiwari, "Analysis of Subsurface Soil Radon with the Environmental Parameters and Its Relation with Seismic Events," Journal of the Geological Society of India, vol. 99, no. 6, pp. 847–858, Jun. 2023, doi: https://doi.org/10.1007/s12594-023-2392-z.
[64]K. S. Mwitondi, Ibrahim Al Sadig, Rifaat Hassona, C. Taylor, and A. Yousef, "Statistical Estimate of Radon Concentration from Passive and Active Detectors in Doha," Data, vol. 3, no. 3, pp. 22–22, Jun. 2018, doi: https://doi.org/10.3390/data3030022.
[65]J. S. Viglietti et al., "From nuclear track characterization to machine learning based image classification in neutron autoradiography for boron neutron capture therapy," PLOS ONE, vol. 18, no. 12, pp. e0293891–e0293891, Dec. 2023, doi: https://doi.org/10.1371/journal.pone.0293891.
[66]J. A. Moral-Muñoz, E. Herrera-Viedma, A. Santisteban-Espejo, and M. J. Cobo, "Software tools for conducting bibliometric analysis in science: An up-to-date review," Profesional De La Informacion, vol. 29, no. 1, Jan. 2020, doi: https://doi.org/10.3145/epi.2020.ene.03.
[67]S. Kumar, N. Pandey, Weng Marc Lim, Akash Nil Chatterjee, and N. Pandey, "What do we know about transfer pricing? Insights from bibliometric analysis," Journal of Business Research, vol. 134, pp. 275–287, Sep. 2021, doi: https://doi.org/10.1016/j.jbusres.2021.05.041.
[68]Y. Guo, Z. Hao, S. Zhao, J. Gong, and F. Yang, "Artificial Intelligence in Health Care: Bibliometric Analysis," Journal of Medical Internet Research, vol. 22, no. 7, pp. e18228–e18228, Jul. 2020, doi: https://doi.org/10.2196/18228.
[69]Raminta Pranckutė, "Web of Science (WoS) and Scopus: The Titans of Bibliographic Information in Today's Academic World," Publications, vol. 9, no. 1, pp. 12–12, Mar. 2021, doi: https://doi.org/10.3390/publications9010012.
[70]Sayantan Khanra, A. Dhir, P. Kaur, and Matti Mäntymäki, "Bibliometric analysis and literature review of ecotourism: Toward sustainable development," Tourism Management Perspectives, vol. 37, pp. 100777–100777, Jan. 2021, doi: https://doi.org/10.1016/j.tmp.2020.100777.
[71]P. Khurana and K. Sharma, "Impact of h-index on authors ranking: A comparative analysis of Scopus and WoS," arXiv.org, 2021. https://arxiv.org/abs/2102.06964 (accessed Feb. 01, 2024).
[72]Miguel-Angel Vera-Baceta, M. Thelwall, and Kayvan Kousha, "Web of Science and Scopus language coverage," Scientometrics, vol. 121, no. 3, pp. 1803–1813, Oct. 2019, doi: https://doi.org/10.1007/s11192-019-03264-z.

[73]L. Cori, O. Curzio, G. Donzelli, E. Bustaffa, and F. Bianchi, “A Systematic Review of Radon Risk Perception, Awareness, and Knowledge: Risk Communication Options,” Sustainability, vol. 14, no. 17, pp. 10505–10505, Aug. 2022, doi: https://doi.org/10.3390/su141710505.

[74]A. Giraldo-Osorio, A. Ruano-Ravina, L. Varela-Lema, J. M. Barros-Dios, and Mónica Pérez-Ríos, “Residential Radon in Central and South America: A Systematic Review,” International Journal of Environmental Research and Public Health, vol. 17, no. 12, pp. 4550–4550, Jun. 2020, doi: https://doi.org/10.3390/ijerph17124550.

[75]Meghdad Pirsaheb, F. Najafi, T. Khosravi, and L. Hemati, “A Systematic Review of Radon Investigations Related to Public Exposure in Iran,” Iranian Red Crescent Medical Journal, vol. 15, no. 11, Nov. 2013, doi: https://doi.org/10.5812/ircmj.10204.

[76]S. M. Khan, J. Gomes, and D. R. Krewski, “Radon interventions around the globe: A systematic review,” Heliyon, vol. 5, no. 5, pp. e01737–e01737, May 2019, doi: https://doi.org/10.1016/j.heliyon.2019.e01737.

[77]María Torres-Durán, Juan Miguel Barros-Dios, A. Fernández-Villar, and A. Ruano-Ravina, “Residential radon and lung cancer in never smokers. A systematic review,” Cancer Letters, vol. 345, no. 1, pp. 21–26, Apr. 2014, doi: https://doi.org/10.1016/j.canlet.2013.12.010.

[78]Justin Zuopeng Zhang, Praveen Ranjan Srivastava, D. Sharma, and Prajwal Eachempati, “Big data analytics and machine learning: A retrospective overview and bibliometric analysis,” Expert Systems with Applications, vol. 184, pp. 115561–115561, Dec. 2021, doi: https://doi.org/10.1016/j.eswa.2021.115561.

[79]Jesús López Belmonte, Adrián Segura-Robles, Antonio-José Moreno-Guerrero, and María Elena Parra-González, “Machine Learning and Big Data in the Impact Literature. A Bibliometric Review with Scientific Mapping in Web of Science,” Symmetry, vol. 12, no. 4, pp. 495–495, Mar. 2020, doi: https://doi.org/10.3390/sym12040495.

[80]A. Helena and Araújo, Wagner Junqueira, “Prospective scenarios: systematic review at Lisa, Emerald, Scopus and Web of Science,” Lareferencia.info, 2020. https://www.lareferencia.info/vufind/Record/BR_9b7afa48e19ba6a31973df6a7ebb8491 (accessed Feb. 02, 2024).

[81]Naveen Donthu, S. Kumar, D. Mukherjee, N. Pandey, and Weng Marc Lim, “How to conduct a bibliometric analysis: An overview and guidelines,” Journal of Business Research, vol. 133, pp. 285–296, Sep. 2021, doi: https://doi.org/10.1016/j.jbusres.2021.04.070.

[82]K. Goyal and S. Kumar, “Financial literacy: A systematic review and bibliometric analysis,” International Journal of Consumer Studies, vol. 45, no. 1, pp. 80–105, Aug. 2020, doi: https://doi.org/10.1111/ijcs.12605.

[83]A. Tandon, P. Kaur, Matti Mäntymäki, and A. Dhir, “Blockchain applications in management: A bibliometric analysis and literature review,” Technological Forecasting and Social Change, vol. 166, pp. 120649–120649, May 2021, doi: https://doi.org/10.1016/j.techfore.2021.120649.