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Bibliometric Analysis of Prostate Cancer and Deep Learning[1]

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Abstract

The metallurgical industry is facing growing pressure to adopt sustainable practices due to environmental concerns and resource depletion. This paper explores recent advancements in green processing technologies, metal recycling, and the development of eco-friendly alloys. Key innovations include energy-efficient extraction techniques, circular economy approaches, and sustainable alloy design. These developments are crucial for reducing carbon footprints and ensuring resource efficiency. This study highlights industry best practices, emerging technologies, and future directions for sustainable metallurgy. And also aims to bring together researchers, industry experts, and policymakers to explore the latest advancements in sustainable metal production. By fostering collaboration and knowledge exchange, this event will contribute to shaping a greener, more resilient metallurgical industry that meets the demands of the future.

Keywords: Prostate Cancer, Deep Learning, Bibliometric Analysis, Lda Analysis, Louvain Algorithm

INTRODUCTION

Prostate cancer is one of the most common cancers in men worldwide and remains a major public health challenge [1,2]. With a high incidence rate, particularly in developed countries, it is the second most common cancer in men. Prostate cancer remains a major cause of cancer-related morbidity and mortality, despite improvements in diagnosis and treatment[3,4]. To improve patient outcomes and reduce the burden of disease, early detection, accurate staging and personalised treatment plans are essential [5]. Traditional diagnostic modalities for prostate cancer, including prostate-specific antigen (PSA) testing, digital rectal examination (DRE) and biopsy, have limitations in terms of accuracy, sensitivity and specificity[6]. These issues have led to the exploration of advanced technologies, including medical imaging, genomic profiling, and artificial intelligence (AI), to improve diagnostic accuracy and treatment planning. Deep learning uses multi-layer neural networks to automatically identify and extract significant patterns from complicated

[1] This study is presented in 20. Th MAS Congress.

and high-dimensional data [7, 8]. It is particularly useful in cancer research because of its ability to process massive amounts of data with little human intervention. Deep learning has been used in the context of prostate cancer for several tasks, including survival analysis, treatment response prediction, automated tumour diagnosis and medical image segmentation. In addition to improving diagnostic accuracy, these applications open the door to precision medicine, where drugs are personalised to each patient's unique characteristics. In order to fully investigate the state of research on the use of deep learning in prostate cancer, this study aims to perform a bibliometric analysis [9, 10]. A quantitative technique called bibliometric analysis examines academic publications to find trends, links and key papers in a particular topic. In order to provide a comprehensive picture of the current situation, this analysis will highlight key trends, well-known authors, prestigious universities and innovative fields of study. By bridging the gap between AI and oncology, this study aims to help researchers, physicians and policymakers harness the potential of deep learning to improve patient outcomes and reduce the global impact of prostate cancer.

METHODOLOGY

This study utilized a bibliometric approach to analyze the current state of deep learning applications in prostate cancer research. Relevant publications from PubMed indexed between 2013 and 2025 were retrieved using the query “prostate cancer” AND “deep learning”, focusing on studies that integrated AI-based techniques in diagnostics, imaging, treatment planning, and biomarker discovery.

The analysis consisted of the following methodological steps:

1. **Data Extraction**: Bibliographic records including titles, authors, journals, years, and keywords were exported and formatted for analysis.
2. **Keyword Co-occurrence Network**: Using *VOSviewer*, keyword frequency and relationships were visualized to reveal prominent research clusters. Low-frequency terms were excluded using a threshold.
3. **Topic Modeling**: The *Latent Dirichlet Allocation (LDA)* algorithm was applied to research paper titles to extract abstract topics. After preprocessing the text (tokenization, lowercasing, stop-word removal), topic coherence scores were used to determine the optimal number of topics. Visualization was performed with *pyLDAvis.*
4. **Community Detection**: To analyze research collaboration, co-authorship networks were constructed using *NetworkX*, and *the Louvain algorithm* was used for community detection. Author nodes and their edges (joint publications) were evaluated for modular clustering.

These combined techniques provided a rich understanding of thematic trends, keyword evolution, and author collaborations in prostate cancer AI research.

RESULTS

To conduct a comprehensive bibliometric analysis, we examined publications indexed in PubMed under the Medical Subject Headings (MeSH) term "prostate cancer" between 2013 and 2025. The focus was specifically on studies applying deep learning techniques to prostate cancer. A structured search strategy was used to retrieve relevant articles. A targeted search of PubMed using the keywords "prostate cancer" AND "deep learning" was performed to collect bibliographic records for analysis. The exported dataset included key metadata such as title, authors, journal, year of publication and keywords, and was saved in .txt format for processing.

The bibliometric data were analysed using VOSviewer (version 1.6.20), a tool designed to construct and visualise bibliometric networks, including co-authorship, co-citation and keyword co-occurrence maps. Once the dataset was loaded into VOSviewer, the software extracted and examined relevant fields such as author names, publication years, citation counts and keyword frequencies.

The annual publication trend is shown in Figure 1, where the x-axis represents the years and the y-axis represents the number of publications per year. The trend shows a clear increase in research activity over time, particularly from 2020 onwards, with a notable peak of 133 publications in 2021. This upward trend reflects the growing role of deep learning in prostate cancer research, driven by advances in AI algorithms and their integration into medical imaging, diagnosis and treatment planning.

PubMed was selected as the primary data source because of its broad coverage of biomedical and clinical research, its inclusion of peer-reviewed literature, and its use of standardised MeSH indexing, which ensures higher relevance and precision of search results. However, we acknowledge that other databases such as Web of Science, Scopus and Embase could enrich the analysis by providing a broader, interdisciplinary perspective.

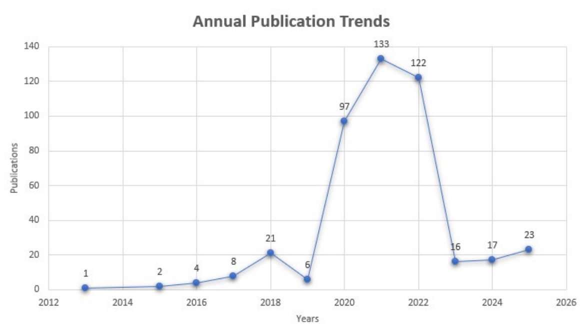


Figure 1: Yearly publishing trends

To identify emerging research themes and patterns of collaboration, keywords were analysed for co-occurrence and authors were mapped based on shared authorship links. Highly cited papers were identified to highlight influential contributions. To ensure clarity, low-frequency keywords were filtered out by applying a minimum occurrence threshold. Related terms were grouped into thematic clusters using the VOSviewer clustering algorithm. In the final visualisation, node size reflects keyword frequency, while link strength indicates the strength of co-occurrence relationships. The layout was optimised to improve the interpretability of the network.

Vosviever

Figure 2 is generated using VOSviewer, is a keyword co-occurrence network that visually maps the major research themes in the field of deep learning applications in prostate cancer. Each node represents a keyword extracted from the bibliographic dataset, and larger nodes indicate keywords that appear more frequently in the literature. Edges (lines) between nodes represent co-occurrence relationships—how often two terms appear together in the same article—while the proximity of nodes reflects the strength of their association.

"Deep learning" is the most dominant keyword, located at the center with the largest node size, indicating it is the core term in nearly all documents. Closely related keywords such as "artificial intelligence", "machine learning", and "magnetic resonance imaging" are also highly prominent, forming dense clusters around the central theme.

Color-coded clusters represent thematic groupings discovered through co-occurrence analysis. For example: The red cluster includes terms related to computational pathology, biopsy, histopathology, and image classification—focusing on cancer detection and grading.The green cluster revolves around radiotherapy planning, dose prediction, and treatment modeling, indicating research into therapeutic optimization. The purple cluster emphasizes imaging techniques, including CT, PET, segmentation, and adaptive radiotherapy. The yellow and orange clusters highlight terms related to genomics, biomarkers, survival analysis, and AI-assisted decision support.

This visual representation helps identify central research areas, emerging subfields, and interdisciplinary overlaps. For instance, intersections between radiomics, prostate segmentation, and AI models suggest growing interest in combining imaging and AI for precision oncology.

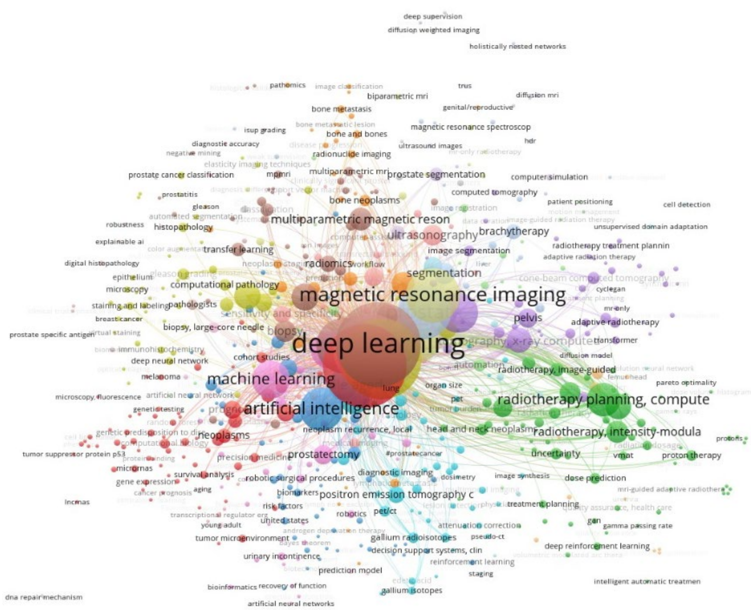


Figure 2: Network of keywords

The co-occurrence map offers a comprehensive overview of the knowledge structure in this research domain. It enables researchers to quickly detect influential topics, identify potential gaps, and understand how concepts are interconnected in the context of prostate cancer and deep learning.

Topic Modeling With Latent Dirichlet Allocation (LDA)

A popular generative statistical model in natural language processing (NLP) for identifying abstract subjects in massive text databases is LDA. It assumes that every document has several subjects, each of which is represented by a word distribution. Using LDA on the titles of research papers in our dataset, we hope to determine the main research topics at the nexus of deep learning and prostate cancer, determine the most important terms linked to each theme, offering hints about areas of research interest, to see how several subjects relate to one another, visualize topic distributions.

Research paper titles about deep learning and prostate cancer that were taken from pertinent bibliographic sources make up the dataset used in this analysis. Tokenization, lowercasing, and stop-word removal are text cleaning techniques that guarantee significant subject extraction. A corpus represents texts as a bag of words, and a dictionary is created to map unique words to indexes. A predetermined number of themes are extracted from the corpus by training the LDA model, which is based on an evaluation of the coherence score. To examine the identified themes, we create an interactive visualization using pyLDAvis that shows topic relationships and keyword distributions.

Using LDA on this dataset, we hope to find important topics like:

1. Deep Learning in Prostate Cancer Imaging (e.g., MRI-based diagnosis, biopsy image classification).

2. AI-assisted Treatment Decision Support (e.g., risk prediction models, personalized medicine).

3. Predictive Modeling for Prognosis (e.g., survival analysis, recurrence prediction).

4. Integration of Genomic and Clinical Data (e.g., AI-driven biomarker discovery).

5. Automated Segmentation and Detection (e.g., AI-based tumor detection in medical scans).

The findings of this analysis offer a well-organized summary of the state of deep learning and prostate cancer research, assisting in the identification of knowledge gaps and new developments in the area. Further insights into the development and potential paths of AI applications in oncology can be gained by applying the subject modeling approach employed here to other areas of medical AI research.

Algorithm: LDA_Topic_Modeling

Input: CSV file with a column 'Title' containing text data

Output: Printed LDA topics and saved pyLDAvis HTML visualization

1. Load the CSV file into a DataFrame

2. Preprocess each document in the list

3. Create a dictionary of unique words from the tokenized texts

4. Convert each document into a bag-of-words representation using the dictionary

5. Define number of topics to extract

6. Train the LDA model using the corpus and dictionary:

7. Print each discovered topic and associated keywords

8. Generate an interactive topic visualization using pyLDAvis

9. Save the visualization as an HTML file (e.g., 'lda_visualization2.html')

LDA_Topic_Modeling algorithm performs topic modeling on a collection of research paper titles using Latent Dirichlet Allocation (LDA). It starts by preprocessing the text (lowercasing and tokenizing), then converts it into a bag-of-words format. An LDA model is trained to uncover hidden thematic topics by identifying common word patterns across documents. The resulting topics are printed and visualized using pyLDAvis, which creates an interactive HTML plot showing how topics relate and what keywords define them. This process helps researchers explore major research themes and trends in large text datasets.

The visualization highlights key thematic areas such as *"Deep Learning in Cancer," "Prostate Cancer Diagnosis," "AI in Medical Imaging," and "Cancer Treatment Prediction."* These topics represent the dominant research themes within the dataset and reflect evolving trends in the application of deep learning to prostate cancer, shedding light on the primary directions of scientific inquiry in the field.

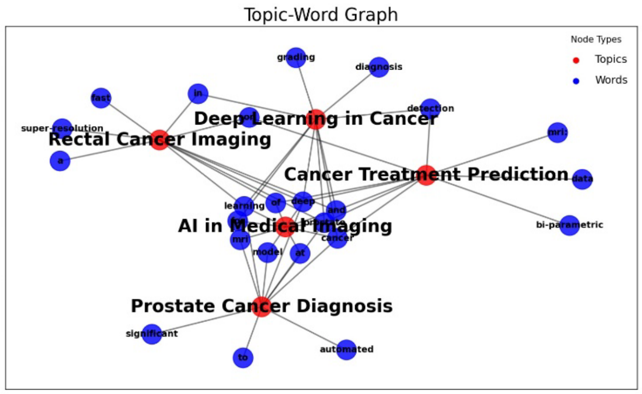
A total of ten representative papers were examined and classified into major research domains, including:

- Automated Prostate Cancer Diagnosis – AI-powered methods for detecting and classifying cancerous regions in MRI and biopsy images.
- Predictive Models for Treatment Response – Deep learning models designed to forecast the effectiveness of radiotherapy and chemotherapy.
- Genomics and Biomarkers in Prostate Cancer – AI-assisted identification of key molecular markers, genetic alterations, and associated risk factors.
- Medical Image Processing – Advanced imaging techniques for enhancing MRI, ultrasound, and histopathological scans to improve diagnostic accuracy.
- AI-Based Decision Support Systems – Integration of machine learning into clinical workflows to support oncologists in making treatment decisions.

The primary technique employed for uncovering hidden thematic patterns in the dataset was Latent Dirichlet Allocation (LDA). LDA is a probabilistic modeling approach that assumes each document contains multiple topics, with each topic characterized by a specific distribution of words. In this bibliometric study, LDA proved effective in revealing underlying research structures and relationships, enabling a systematic overview of how deep learning is being applied in prostate cancer research.

While Non-negative Matrix Factorization (NMF) is another commonly used topic modeling method, it was not selected in this case due to its reliance on matrix factorization, which tends to produce less stable topic boundaries in large and sparse datasets. In contrast, LDA's strength lies in its ability to model topic-word distributions probabilistically and represent hierarchical topic relationships, making it more suitable for the structure of our dataset.

To optimize the performance of the LDA model, a grid search was conducted to identify the best parameters for topic separation. Topic coherence scores were used to determine the most interpretable and distinct number of topics. Based on these evaluations, five topics were identified as the ideal number—striking a balance between comprehensive coverage of the research landscape and maintaining thematic clarity. Multiple training iterations were applied to ensure stable clustering and consistent topic distribution across the corpus, further strengthening the reliability of the findings.



Şekil 3: Topic-word graph

The distribution of study themes and their relationships are depicted in the figure 3 produced by LDA. Among the visualization's main highlights are distinct deep learning research clusters for prostate cancer, distribution of keywords within each subject, illuminating key areas of research, links between topics, showing how many study subjects intersect and change throughout time.

Community Detection With The Louvain Algorithm

To analyze the collaborative networks among researchers, we applied the Louvain algorithm, a community detection method that optimizes modularity to identify densely connected groups of nodes in a network. In this case, co-authorship ties are represented by the edges, while authors are represented by the nodes. The networkx package was used to create the co-authorship graph. The authors of each paper were taken out and linked together by edges, which symbolized their working relationships. The graph was then divided into communities using the Louvain algorithm, each of which represents a collection of authors who constantly work together. A color-coded network graph (Figure 3), in which nodes that belong to the same community are assigned the same color, was used to illustrate the resulting communities.

Algorithm: Bibliometric Analysis of Deep Learning in Prostate Cancer

Input: PubMed-indexed articles (2013–2025) using the query: "prostate cancer" AND "deep learning"

Output: Research trends, topic models, author communities, and keyword clusters

1. Data Collection: Retrieve metadata (title, authors, keywords, year) from PubMed using MeSH filtering.
2. Preprocessing: Tokenize and lowercase titles; remove stopwords; build bag-of-words model.
3. Topic Modeling (LDA): Train Latent Dirichlet Allocation with optimized topic number using coherence scores. Extract major topics and visualize with pyLDAvis.

4. Keyword Analysis (VOSviewer): Build co-occurrence networks; identify clusters representing key research domains.
5. Community Detection (Louvain): Construct co-authorship graph; apply Louvain algorithm to detect research communities.Visualize with colored network graphs.
6. Interpretation: Analyze topic-word relations, community structures, and keyword clusters to identify trends and gaps in prostate cancer AI research.
7. Bibliometric Analysis of Deep Learning in Prostate Cancer

Bibliometric Analysis of Deep Learning in Prostate Cancer algorithm outlines a structured approach to bibliometric analysis of deep learning applications in prostate cancer. It begins by collecting relevant articles from PubMed using a targeted keyword query, followed by text preprocessing and topic modeling through Latent Dirichlet Allocation (LDA) to uncover major research themes. Keyword co-occurrence is analyzed using VOSviewer to identify thematic clusters, while co-authorship networks are constructed and analyzed using the Louvain algorithm to detect collaborative research communities. The results are visualized through topic-word graphs and community maps, offering insights into evolving trends, influential authors, and emerging focus areas within the field.

The Latent Dirichlet Allocation (LDA) model revealed five distinct research topics, each defined by its top 10 most representative keywords. Topic 0 includes general linguistic connectors like "and," "of," and "in," alongside domain-relevant terms such as "learning," "cancer," "deep," and "prostate," indicating a broad overview of deep learning in cancer contexts. Topic 1 is characterized by terms like "data," "MRI," "improve," and "learning," pointing to themes related to imaging data enhancement and analytical techniques. Topic 2 highlights technical imaging processes, with keywords such as "super-resolution," "motion-robust," "reconstruction," and "biologically," suggesting a focus on image optimization and biological interpretability in prostate cancer studies. Topic 3 revolves around medical imaging and cancer detection, with frequent terms including "MRI," "detection," "bi-parametric," and "model," reflecting research on automated diagnosis using imaging techniques. Topic 4 focuses on diagnostic imaging methods with words like "contrast-enhanced," "multiparametric," "resonance," and "magnetic," indicating detailed exploration of MRI-based prostate cancer detection.

The Louvain algorithm was applied to the co-authorship network to identify collaborative communities within the research corpus. The results revealed multiple distinct author groups, each representing a densely connected research community. Community 0 includes authors such as Hamm CA, Baumgärtner GL, and Biessmann F, indicating a well-established collaboration cluster. Community 1 features Zhang YF, Zhou C, and Guo S, suggesting a separate network possibly centered in East Asian institutions. Community 2 contains names like Bischoff LM, Peeters JM, and Weinhold L, showing another prominent collaboration likely based in European clinical research. Community 3, with members like Elmarakeby HA and Hwang J, may be more genomics-focused based on related affiliations. Similarly, smaller communities like Community 4, 5, 6, 7, and 8 include regionally or topically aligned researchers, reflecting the global and interdisciplinary nature of deep learning research in prostate cancer.

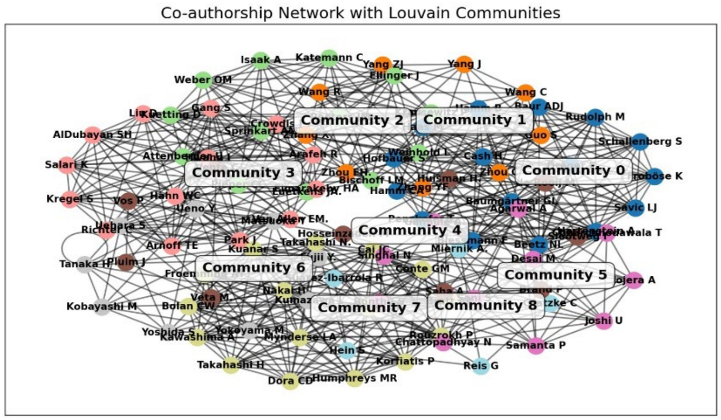


Figure 4: Louvian algorithm - graphical result

Figure 4 illustrates the collaborative structure among researchers working on deep learning applications in prostate cancer. The network was generated based on co-authorship relationships extracted from scientific publications. Each node represents an individual author, and each edge indicates that the connected authors have co-authored at least one paper.

The Louvain algorithm was used to detect modular communities—groups of authors who collaborate more closely with each other than with authors outside their group. These communities are visualized using color-coded clusters, and the major communities are labeled as Community 0 to Community 8.

Key points from the visualization: Dense connectivity within each community indicates strong intra-group collaboration. Community 0 and Community 1 are among the most tightly knit, possibly representing prolific research hubs in North America and East Asia, respectively. The central layout suggests that some communities (e.g., Community 4 or 6) act as bridges connecting multiple clusters, indicating interdisciplinary or inter-institutional collaboration.

The Kamada-Kawai layout used in the visualization optimizes node positioning to reflect structural relationships clearly and reduce overlap. Overall, this network highlights the global and collaborative nature of AI-based research in prostate cancer and offers valuable insight into how expertise is distributed and shared among leading contributors in the field.

The use of Latent Dirichlet Allocation (LDA) and the Louvain algorithm provided valuable insights into the research landscape of deep learning in prostate cancer. The LDA model successfully identified key thematic areas aligned with current trends—such as *“Deep Learning in Cancer”* and *“Prostate Cancer Imaging”*—demonstrating the effectiveness of advanced text mining methods in uncovering hidden patterns within large scientific corpora.

To analyze collaborative structures, the Louvain algorithm was employed as the primary community detection method. This algorithm is particularly well-suited for large and complex co-authorship networks because it efficiently detects groups of closely connected researchers by optimizing modularity—a measure of how well a network is divided into distinct communities. Compared to other methods like Girvan-Newman and Leiden, Louvain offers greater scalability and computational efficiency. While Girvan-Newman is computationally expensive due to recursive edge removal, and Leiden requires more iterations to stabilize, Louvain achieves high-quality clustering with lower computational cost.

Modularity plays a central role in assessing the quality of the community structure. The Louvain algorithm operates by iteratively forming clusters in which internal connections (co-authorship ties) are denser than connections to other groups. This results in coherent representations of collaborative groups. Moreover, it supports hierarchical community detection, allowing smaller research teams to be grouped under larger, overarching scientific communities—ideal for modeling academic networks.

To enhance accuracy and robustness, the co-authorship graph was constructed using specific thresholds:

- Node Size: Represents the number of publications by each author.
- Edge Weight: Represents the number of joint publications between two authors.
- Minimum Edge Threshold: Weak links (with fewer than two co-authored papers) were filtered out.

The graph was visualized using the Kamada-Kawai layout to improve node spacing and interpretability. Each identified community was assigned a distinct color for clarity, and the overall modularity score was used to validate the quality of the clustering.

As a result, nine unique research communities were identified, each representing a major focus area within the domain of prostate cancer and deep learning. In contrast, the Girvan-Newman method identified only four groups due to computational limitations, and the Leiden algorithm, while effective, was more resource-intensive. These findings demonstrate that the Louvain algorithm is a highly effective and efficient choice for detecting research communities in large-scale bibliometric studies.

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