Intellectual Property Protection in the Age of AI: From Perspective of Deep Learning Models

Jing Li*, Quanwei Huang
School of Law, Henan University of Science and Technology, Henan, China

Abstract*—The rapid development of Artificial Intelligence (AI), especially Deep Learning (DL) technologies, has brought unprecedented challenges and opportunities for Intellectual Property (IP) protection and management. In this paper, we employ Bibliometrix and Biblioshiny to conduct a bibliometric analysis of global research at the intersection of AI-driven innovation and IP frameworks over the past decade. The findings reveal a significant annual growth rate of 15.34 per cent in publications, with an average of 5.82 citations per study, reflecting increasing academic interest. China, the United States, and India dominate the research output, but the cross-country collaboration rate is only 10.74 per cent, indicating that there is still room for improvement in global collaborative research. The current major research groups in the field, as well as different research themes, are identified through collaborative network and thematic analyses, respectively. Although the field has achieved remarkable results in technological innovation, the deep integration of legal, economic and ethical dimensions is still at an early stage. The study highlights the urgent need for interdisciplinary collaboration and enhanced international cooperation to address pressing issues such as AI-generated content (AIGC) attribution, legal applicability, and the societal impact of DL technologies in IP protection. These findings aim to support academia and industry in clarifying ownership and promoting synergistic innovation in the AI era.

Keywords—Intellectual property; Artificial Intelligence; Deep Learning; Natural Language Processing; neural network; legal applicability

I. Introduction

With the deepening of the digital economy and information society, the protection and management of intellectual property (IP) has become increasingly prominent. The traditional IP system is mainly constructed on the basis of the original contribution of human creators, mainly covering copyright, patent, trademark and protection measures related to original content, and its core lies in guaranteeing the exclusive right of creators to intellectual achievements [1]. However, the changes in content dissemination and the accelerated speed of information dissemination brought about by the digitalization era have made it difficult for traditional means of protection to meet the increasingly complex problems of copyright infringement, content tampering and illegal copying. Digital content protection technology has therefore emerged, and its basic goal is to protect digitized information through technical means, ensuring the integrity and authenticity of content in the process of transmission, storage and use [2].

In recent years, the rapid development of Artificial Intelligence (AI) technology has greatly promoted changes in various fields. In the context of the AI era, IP issues also reflect many new features. The emergence of AI-Generated Content (AIGC) has made the attribution of intellectual property rights such as copyrights, patents and trademarks extremely complex [3]. DL models represented by Generative Adversarial Networks (GANs), Diffusion Models, and Transformer are capable of generating highly realistic images, audio, video, and text, which not only bring new development opportunities for the cultural and creative industries, but also raises a series of legal and ethical issues, such as the identification of "creators", the attribution of copyright, and the division of responsibility [4].

In the traditional IP field, the application of DL has shown great positive effects. In patent classification and retrieval, traditional patent databases are huge and text lengthy, and there are limitations in manual classification and keyword matching methods. Natural language processing (NLP) based on DL (e.g., BERT, Siamese Network) can automatically parse patent text, perform accurate classification and semantic matching, and improve the efficiency and accuracy of patent retrieval. For example, Chen et al. [5] proposed a DL-based patent retrieval framework that leverages entity recognition and semantic relation extraction, and achieved better accuracy than traditional methods by efficiently extracting fine-grained information. In terms of digital copyright monitoring and infringement detection, using models such as convolutional neural networks (CNNs) and visual transformer (ViT), feature extraction and matching can be performed on digital media such as pictures, videos, and audios to realize automatic detection of infringement. Fang [6] proposed a copyright management system that combines deep belief network (DBN) and blockchain technology to identify and track copyright-protected music content. Lin [7] proposed a CNN-based framework for copyright protection and risk assessment in literary works. The model detects potential copyright infringements by identifying substantial overlaps and stylistic similarities with registered content. In trademark identification and infringement analysis, the DL model can automatically identify similar or counterfeit trademarks by extracting visual features, assisting in determining the risk of confusion and effectively protecting brand image. Alshowaish et al. [8] proposed a trademark similarity detection system based on VGGNet and ResNet to retrieve trademarks based on shape similarity to facilitate and improve the accuracy of the examination process.

Meanwhile, researchers are committed to solving new problems in the AI era through DL models. In terms of traceability and marking of AIGC, DL techniques help to trace the origin of generated content by embedding digital watermarks

*Corresponding Author.

or identifiers of generated content (e.g., through invisible watermarking techniques) to solve the problems of copyright attribution and prevention of misuse. Rouhani et al. [9] proposed an end-to-end IP protection framework that protects the IP rights of owners of neural network architectures by inserting coherent digital watermarks. In terms of technological innovation trend prediction, DL technology can mine global patent data and technical literature to predict future technological hotspots and innovation trends, and assist enterprises in strategic planning and decision-making. Jiang et al. [10] proposed a DL framework for predicting patent application outcome by mining and fusing the features of text content and context networks. In addition, in the context of integrated IP management, the multimodal DL model is able to identify infringements and improper uses in cross-media environments through the joint understanding of text, image and video information. Li et al. [11] constructed a multimodal large-scale dataset for strictly annotated product patent infringement detection, examined the performance of different DL models in detecting potential patent infringements, and proposed a simple and effective infringement detection process.

However, as technology continues to evolve, new technologies bring convenience and efficiency while also raising new legal risks and challenges. First, in order to train DL models, it is usually necessary to rely on a large amount of data, which may contain a large amount of copyrighted material, and the problem of unauthorized use of data exacerbates the risk of copyright infringement to a certain extent [12]. Second, the misuse of deep generative models, such as the dissemination of falsified images, videos, and false information, also poses a serious test of existing legal regulation and ethical norms. Issues such as the reversibility of digital watermarking, privacy leakage, and technology abuse have gradually emerged, exacerbating the lag of traditional IP laws and policies in responding to the impact of emerging technologies. The diversified applications of AI in the form of Sora, Midjourney and Stable Diffusion have greatly reduced the technical threshold and economic cost of knowledge production, but also blurred the boundaries between originality and imitation, posing potential infringement risks to the traditional IP protection system constructed on the basis of “human creation”. This is a potential infringement risk to the traditional intellectual property protection system based on “human creation” [13]. Finally, the “black box” nature of DL models makes the definition of responsibility blurred in the event of infringement, misjudgment or disputes, which is particularly prominent in the attribution of AIGC and infringement disputes [14]. Therefore, how to effectively avoid the potential risks of DL technology while utilizing its advantages has become an important issue in today's IP research.

Based on the above background and status quo, this study is based on bibliometric methodology and utilizes Bibliometrix and Biblioshiny tools to systematically sort out and quantitatively analyze AI-driven IP (AID-IP) research in the past decade from the perspective of DL models. First, the bibliometric study can reveal the overall structure, hot topics, and knowledge evolution trends of the research in this field, and grasp the cross-fertilization between different disciplines. Second, the bibliometric study can help identify high-impact literature, core journals, and key research groups, and clarify which DL methods have made breakthroughs in IP applications, and what technical and legal issues remain to be resolved. Finally, this study not only provides a basis for quantitative evaluation of existing research, but also provides data support for future policy formulation, improvement of regulatory mechanisms, and deepening of interdisciplinary research.

This research aims to address the following key questions:

Q1: Over the past decade, what has been the trend in the number of publications, citation patterns, and core journals in AID-IP research? Can the evolution of these themes reveal emerging IP challenges in the context of AI era?

Q2: What differences can be observed in the contributions of different countries or regions to AID-IP research, based on geographic distribution and collaboration network data? What implications do these differences have for global IP protection strategies?

Q3: In the context of the AI era, what specific areas does DL technology cover in IP applications? What are the most prominent challenges in each subfield?

Q4: Based on the thematic analysis results, is there a gap in the literature regarding the application of DL technology in IP protection and its discussion within the context of IP laws and policy frameworks? What theoretical or practical shortcomings does this gap reflect? How should future research break through existing theoretical frameworks to better address the needs of technological development and legal regulation?

These research questions not only provide a quantitative overview of technological advancements in the AID-IP domain from a bibliometric perspective but also delve into interdisciplinary intersections, theoretical gaps, and legal and policy challenges in a globalized context. Traditional literature has primarily focused on algorithmic optimization and performance validation. However, discussions on the compatibility of DL technologies with existing IP legal frameworks, the ambiguity of their boundaries, and the resulting legal risks remain insufficient. A bibliometric approach is therefore essential to capturing the broader developmental trajectory of this research domain, offering data-driven insights and theoretical foundations for future in-depth studies.

The following sections of this paper are organized as follows: Section II outlines the research methodology, including data collection procedures and the application of bibliometric tools. Section III presents the key findings, focusing on publication trends, citation patterns, geographical distribution, collaboration networks, and thematic developments within AID-IP research. Section IV provides a critical discussion of the results in relation to the research questions posed in the introduction. Finally, Section V concludes the paper by summarizing the main insights, emphasizing both theoretical and practical implications, and suggesting directions for future research.

II. Methods

This study employs a bibliometric approach, leveraging Bibliometrix and Biblioshiny to systematically analyze research on AID-IP protection and management over the past decade. Data is sourced from the Web of Science Core Collection (WoSCC) and Scopus.

A. Dataset Construction

The first step in bibliometric analysis is literature identification and selection. The data collection process is illustrated in Fig. 1.

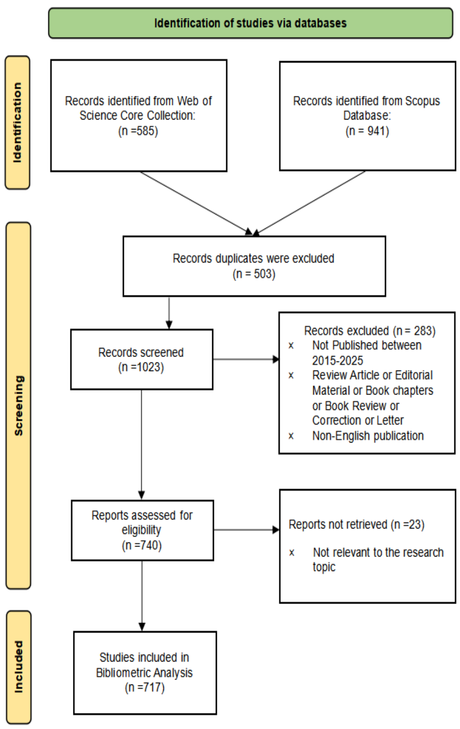

Fig. 1. Flowchart of the dataset collection process.

In this study, WoSCC and Scopus serve as the primary data sources. The search query used is as follows: TI = (("Artificial Intelligence" OR "AI" OR "Deep Learning" OR "Machine Learning" OR "Neural Network") AND ("Intellectual Property" OR "Patent" OR "Copyright" OR "Content Protection" OR "Trademark")). The search was conducted in February 2025 to capture studies at the intersection of AI technologies—including machine learning, neural networks, and generative AI—and IP filed, covering patents, copyrights, trademarks, and digital content protection.

The initial search retrieved 585 records from WoSCC and 941 from Scopus. After removing 503 duplicates, 1,023 unique records remained for further screening.

Studies published outside the 2015-2025 timeframe were excluded from the screening process to ensure that the analysis focused on the most recent advances in AID-IP research. Irrelevant document types including reviews, book chapters, corrections, and letters were excluded. Additionally, non- English publications were removed to maintain consistency in the linguistic analysis. This resulted in 740 documents for further eligibility assessment. Finally, 740 articles were assessed in full text for direct relevance to the research topic of this paper through manual review and discussion between two researchers. 23 studies that passed the initial screening but were not directly relevant to research focus were excluded at this stage. After completing a rigorous screening and eligibility assessment, 717 studies were considered highly relevant and included in the bibliometric analysis. All search results were exported to BibTeX format for standardized processing in Bibliometrix.

B. Bibliometric Analysis Tools

After completing the construction of the dataset, key metrics and network analyses were conducted using Bibliometrix and its web-based interface Biblioshiny in R [15-16]. To assess citation impact, we use Mean Total Citations per Article (MeanTCperArt), calculated as:

$$\text{MeanTCperArt} = \frac{\text{Total Citations}}{\text{Total Articles}} \tag{1}$$

This metric indicates the average scholarly influence of the documents analyzed and supports comparative evaluations across authors, journals, or time periods.

The co-citation network was constructed using a minimum co-citation threshold of 15 to exclude weak relationships and retain frequently co-cited references. The Louvain modularity algorithm was applied to detect thematic clusters based on internal citation strength. The modularity Q is defined as:

$$Q = \frac{1}{2m} \sum_{i,j} [A_{i,j} - \frac{k_i k_j}{2m}]\, \delta(c_i, c_j) \tag{2}$$

where, $A_{i,j}$ is the edge weight between nodes i and j, k_i and k_j are their respective degrees, m is the total number of edges, and $\delta(c_i, c_j)$ is 1 if nodes i and j belong to the same community and 0 otherwise. This formula evaluates how well a network is partitioned into modules with dense internal connections.

Author Keywords occurring at least ten times were used to build the keyword co-occurrence network. Nodes represent keywords, and edges indicate the frequency of co-occurrence in the same document. To assess keyword importance, we applied three centrality measures: PageRank, Betweenness Centrality and Closeness Centrality.

To examine collaboration patterns, we constructed author- level and country-level networks. The Leiden algorithm was used for community detection, offering improvements over Louvain by ensuring community connectivity and faster convergence. It can optimize various objective functions, such as modularity or the Reichardt–Bornholdt (RB) Potts model, expressed as:

$$H = -\sum_{i,j} (A_{ij} - \gamma \cdot P_{ij})\, \delta(c_i, c_j) \tag{3}$$

where, A_{ij} represents the weight of the edge between nodes i and j. P_{ij} is the expected weight of the edge between i and j under a random model, γ is the resolution parameter that adjusts the scale of community detection.

To normalize the collaboration strength, we used the Jaccard similarity coefficient, defined as:

$$\mathrm{Jaccard}(A,B)=\frac{|A\cap B|}{|A\cup B|} \quad (4)$$

For both author and country-level collaborations, only edges with at least two co-authored publications were retained, and isolated nodes were excluded to focus on significant partnerships.

These multilevel and multifaceted analyses provide a clear view of the connections between different studies [16]. Finally, through thematic analysis, the main research directions and hot issues in the field are presented, and the relationship networks and knowledge maps between various themes are drawn, so as to fully grasp the research lineage and future trends.

III. Results

Based on the constructed experimental dataset, this section uses Bibliometrix and Biblioshiny to give the results of basic statistical analysis, collaborative analysis, and thematic analysis of the relevant studies on AID-IP in the last decade, and visualization to intuitively show the complex data relationships, so as to obtain a more detailed interpretation of the academic pulse.

A. General Analysis

Table I gives a quantitative summary of the experimental data. It can be observed that the data comes from 455 different sources including journals, books and conference proceedings, highlighting the interdisciplinary nature of AID-IP research. The annual growth rate of literature publication over the past decade was 15.34%, with an average of 5.824 citations per study, indicating a rapid increase in academic interest in AID-IP research. In addition, the average age of the literature is 3.05 years, attesting to the current activity of the field. The dataset contains 1,833 keywords plus (ID) and 1,623 author keywords (DE), reflecting diverse and rich research topics. The dataset contains 1,647 authors, with a relatively low percentage of single-author papers and an average of 3.07 co-authors per document, reflecting the collaborative and interdisciplinary nature of AID-IP. However, cross-national collaboration only accounts for 10.74 per cent, reflecting the fact that international cooperation is yet to be further improved.

Table II provides a detailed listing of annual publication metrics for the field, including total publication count (N), mean total citations per article (MeanTCperArt), mean total citations per year (MeanTCperYear), and the number of citable years. It can be observed that AID-IP research results show a continuous growth trend, with the number of publications increasing significantly over the years, from 6 articles in 2015 to 192 in 2024. The data for this study was collected from February 2025, so the 2025 data does not reflect the annual trend. MeanTCperArt and MeanTCperYear both peaked in 2018, reflecting the high impact of articles published during this period. The current low citation rate for new research in recent years should not be viewed as a lack of impact, but rather as a delayed citation effect. Overall, the publication metrics reflect a vibrant and expanding field of research that is being shaped by AI, IP, and emerging technologies.

Table III lists the top ten sources contributing the most articles in the field, demonstrating the main platforms for disseminating AID-IP research. It is evident that World Patent Information, Journal of Intellectual Property Law & Practice, and GRUR International are among the top contributors, reflecting the close intersection between AI, IP, patents, and legal frameworks. IIC-International Review of Intellectual Property and Competition Law and Journal of World Intellectual Property further indicate academic interest in the legal, economic, and policy implications of AID-IP. In addition, CEUR Workshop Proceedings, Lecture Notes in Computer Science, IEEE Access, and Lecture Notes in Networks and Systems highlight the significance of AI-driven innovations in IP protection. The top sources reflect the highly interdisciplinary nature of AID-IP research, spanning law, policy, and computer science research. In addition, the conference proceedings play an important role in highlighting the rapidly evolving nature in this area.

TABLE I. Statistical Information of the Dataset

Description	Results
MAIN INFORMATION ABOUT DATA	
Timespan	2015:2025
Sources (Journals, Books, etc)	455
Documents	717
Annual Growth Rate %	15.34
Document Average Age	3.05
Average citations per doc	5.824
DOCUMENT CONTENTS	
Keywords Plus (ID)	1833
Author's Keywords (DE)	1623
AUTHORS	
Authors	1647
Authors of single-authored docs	152
AUTHORS COLLABORATION	
Single-authored docs	168
Co-Authors per Doc	3.07
International co-authorships %	10.74
DOCUMENT TYPES	
Article	457
Article; early access	11
Conference paper	167
Proceedings paper	82

TABLE II. Annual Scientific Production

Year	N	MeanTCperArt	MeanTCperYear	CitableYears
2015	6	1.5	0.14	11
2016	6	4.5	0.45	10
2017	13	9.31	1.03	9
2018	27	29.11	3.64	8
2019	46	6.24	0.89	7
2020	79	11.7	1.95	6
2021	84	9.82	1.96	5
2022	101	5.76	1.44	4
2023	138	2.8	0.93	3
2024	192	1.16	0.58	2
2025	25	0.24	0.24	1

TABLE III. TOP 10 SOURCES

SI.	Sources	Articles
1	World Patent Information	20
2	Journal of Intellectual Property Law & Practice	18
3	Scientometrics	17
4	GRUR International	13
5	CEUR Workshop Proceedings	11
6	IIC-International Review of Intellectual Property and Competition Law	10
7	Lecture Notes in Computer Science	10
8	Journal of World Intellectual Property	9
9	IEEE Access	8
10	Lecture Notes in Networks and Systems	8

Fig. 2 gives the country distribution of AID-IP research over the last decade. Dark blue regions (e.g., China, USA, India) indicate active research activity. Light blue areas (e.g., South America, Africa, and parts of Europe) indicate moderate research participation. Gray areas indicate limited or no research activity in AID-IP. China and the United States occupy the top two positions with 404 and 114 articles, respectively, reflecting the high priority and continued leadership of China and the United States in AI, IP, and patent-related innovation. India ranked third with 75 articles, reflecting its growing influence in AID-IP research.

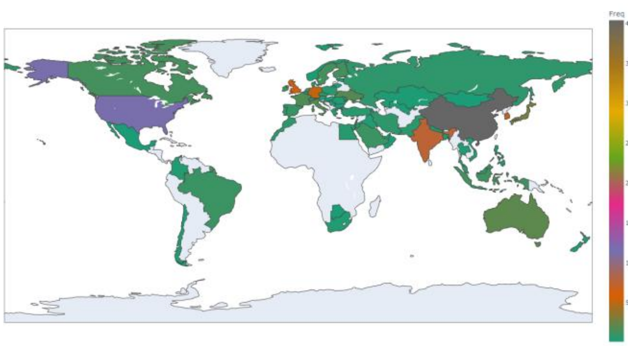

Fig. 2. Geographic distribution.

As can be seen from the results in Fig. 2, China, U.S., and India are leading the way in AID-IP research. Asian countries, particularly China, India, South Korea, and Japan, all rank high in this area, indicating a strong technical and legal focus on AI- driven innovation. Europe has several active contributing countries, including Germany, the UK, France and Italy. The UK is the largest major contributor in Europe with 61 articles, reflecting its strong focus on AI regulations and IP policies. Emerging contributors such as Saudi Arabia and Brazil highlight the growing global interest in AID-IP research.

Academic journals are important platforms for presenting scientific research results, and as the creators of scientific research content, authors affect the competitiveness and influence of journals to a large extent. Therefore, identifying core authors has also become one of the key aspects in intelligence research. Fig. 3 gives the top ten authors with the largest number of publications in AID-IP research. Among them, LIU W, ZHANG Y, and WANG J ranked the top 3 with 16, 14, and 13 articles, respectively, indicating that they have made great contributions and have influence in this field.

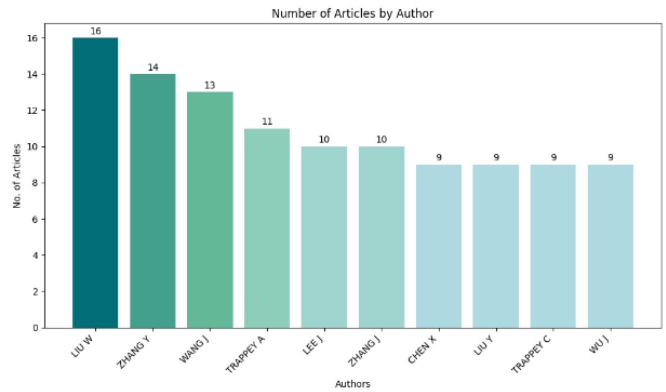

Fig. 3. Most productive authors.

Table IV lists the 10 most cited documents between 2015 and 2025. These high-impact studies not only cover a variety of aspects such as patent classification, technology trend prediction, and IP protection for deep neural networks (DNNs), but also reflect the wide application and continuous evolution of DL technology within this field. In terms of the overall trend, most of the highly cited literature is concentrated in the period from 2018 to 2021, which is closely related to the wide application of DL technology in various fields, and also indicates that IP issues have ushered in unprecedented challenges and opportunities in the era of AI.

From a DL perspective, these studies demonstrate various DL-based technical methods. For instance, Li et al. [17] applied CNN and word embedding techniques for patent classification, highlighting the efficiency of DL in information extraction and text classification. Similarly, Lee and Hsiang [18] showcased the potential of pre-trained language models, specifically BERT, in processing patent literature. Furthermore, concerning the IP protection of DL models themselves, Zhang et al. [19] emphasized the importance of DNN watermarking technology in safeguarding model intellectual property, while Li et al. [20] further validated the role of blind watermark frameworks in proving model ownership. Other studies, such as Cao et al. [21], explored the use of classification boundary fingerprints, which leverage DL's non-linear features and high-dimensional representations to support model protection.

Further analysis reveals that there are not only innovations at the technological level, but some studies also attempt to integrate law, policy and technology. For example, Levendowski [22] explored the role of copyright law in remedying the problem of potential bias in AI, suggesting that the interdisciplinary integration of DL technology and legal regulation in the process of IP protection is becoming an important direction for future research. Meanwhile, Lee et al. [23] showed how multiple patent indicators and machine learning methods can be used to identify emerging technologies in advance, which is important for judging technology trends and guiding industrial decisions.

TABLE IV. TOP 10 MOST CITED ARTICLES

SI.	Title	Citations	Year	Authors
1	Protecting intellectual property of deep neural networks with watermarking	218	2018	Zhang et al.
2	Early identification of emerging technologies: a machine learning approach using multiple patent indicators	136	2018	Lee et al.
3	Forecasting artificial intelligence on online customer assistance: evidence from chatbot patents analysis	121	2020	Pantano & Pizzi
4	DeepPatent: patent classification with convolutional neural networks and word embedding	94	2018	Li et al.
5	Trends and priority shifts in artificial intelligence technology invention: a global patent analysis	86	2018	Fujii & Managi
6	How to prove your model belongs to you: a blind-watermark based framework to protect intellectual property of DNN	78	2019	Li et al.
7	Patent classification by fine-tuning BERT language model	73	2020	Lee & Hsiang
8	IPGuard: protecting intellectual property of deep neural networks via fingerprinting the classification boundary	61	2021	Cao et al.
9	How copyright law can fix artificial intelligence's implicit bias problem	57	2018	LEVENDOWSKI
10	Using supervised machine learning for large-scale classification in management research: the case for identifying artificial intelligence patents	52	2023	Miric et al.

In addition, the temporal distribution and citations of the literature reflect the trend of DL's continuous maturation and proliferation within the IP domain. Early work focused on DL modeling for IP protection, and over time, the research scope has gradually expanded to intelligent classification of patent texts and prediction of technological frontiers, suggesting that researchers are utilizing DL modeling to mine more detailed and multifaceted knowledge information. This trend not only helps to understand the current pulse of technological development, but also lays the foundation for future cross-disciplinary cooperation and exploration of new methods.

B. Network Analysis

Network analysis is a key method in bibliometric research, widely used in the fields of author collaboration networks, national collaboration networks and co-citation networks. Through visualization and quantitative analysis methods, it provides a powerful tool for understanding the complex relationships of scientific research activities and helps to gain insight into the patterns of scholarly communication.

The author collaboration network identifies the core authors, key collaboration groups, and the organizational structure of the research team by analyzing the collaborative relationships among researchers, which provides a basis for the impact assessment and team building of researchers. The author collaboration network of the experimental dataset is shown in Fig. 4. The visualization was generated using the Leiden clustering algorithm, with Jaccard normalization applied to the network data. In the figure different colors are used to distinguish different research groups. The node size is related to the importance of the author in the collaborative network. The connecting line indicates the collaboration between nodes, the thicker the connecting line, the more collaboration between these two authors.

The results reveal that the red cluster is led by Zhang Y, Liu W, and Wang J, represented by larger red nodes and stronger connecting edges. This group focuses on utilizing DL technologies (particularly the features of DNNs) to design embedded watermarking and anti-counterfeiting techniques to ensure model ownership and tamper-proof capabilities [19]. The cluster is concerned with embedding unique identifiers into models, thus providing verifiable evidence in cases of model theft or infringement. This practical approach offers tangible IP protection for the increasingly commercialized AI models, serving as a crucial safeguard for the commercialization of AI products.

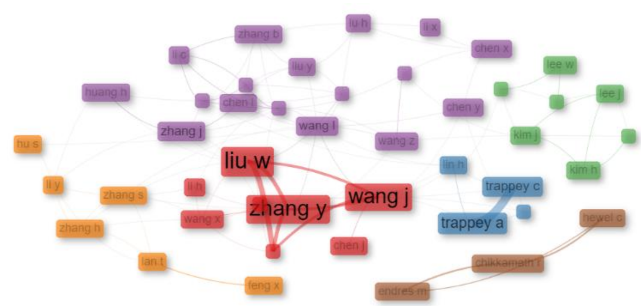

Fig. 4. Collaboration network - Co-authorship between authors.

The purple cluster includes authors like Chen L, Zhang J, and Huang H, who combine DL technologies with traditional IP protection legal frameworks. They explore how data-driven technologies can improve patent classification or technology trend forecasting, while also providing insights for revising legal provisions [24].

The key members of the green cluster include Lee W, Kim J, and Chen Y, who apply advanced DL methods for intelligent processing and trend forecasting of patent data. This cluster provides forward-looking management tools and decision- making support for IP issues within the rapidly changing AI technology field [18], [23].

The blue cluster is led by Trappey C and Trappey A, with a focus on revealing global trends, regional distribution, and industry evolution in AI technology and IP development through big data and patent network analysis. The cluster emphasizes cross-regional strategy and policy discussions [25].

The brown cluster includes authors like Hewel C, Chikkamath R, and Endres-M, who focus on IP issues in specific application scenarios. They examine practical case studies of model, patent, or copyright protection in the commercialization process [26]. This cluster primarily explores innovative applications beyond traditional analytical frameworks, focusing on edge applications and complementary methods.

The national cooperation network can reveal the research cooperation relationship between different countries and explore the global distribution of research resources. The national cooperation network of the experimental dataset is shown in Fig. 5, in which the darker the color, the more research results, and the thicker the line, the closer the cooperation relationship. It can be found that the network presents a hub-and-spoke structure, with China and the United States serving as the central hubs to promote cooperation with multiple countries. Europe forms a dense sub-network characterized by strong intra- regional research partnerships. Emerging AI research countries (e.g., India, Australia, and South Korea), on the other hand, are increasingly integrated into the global network.

Fig. 5. Collaboration network - Co-authorship between countries.

However, there are obvious clusters and imbalances in academic cooperation and exchanges between different countries or regions. Many developing countries or regions have difficulty in participating deeply in global cooperation networks due to the relative lack of research funding, infrastructure and human resources; even if a few researchers are involved in international projects, they are often in a relatively marginalized position. This imbalance is illustrated in the figure by the sparse or almost empty “connecting lines” in some regions. Some marginalized countries are less integrated in global networks. Cooperation between Latin America, Africa and South-East Asia needs to be further strengthened in order to further increase global research equity.

The co-citation network identifies influential classic literature, theoretical foundations, and core research areas by analyzing co-citation relationships between literature. Fig. 6 gives the co-citation network results for the experimental dataset. It can be found that the yellow cluster focuses on the development of DL architectures (CNN, GAN, etc.) and AI innovations [27-30]. The Green cluster focuses on the application of AI in patent analysis, technology forecasting and IP research [31-33]. The blue cluster focuses on legal aspects of AID-IP and policy discussions [34-35]. The red cluster, on the other hand, looks at patent analysis, innovation management and the economic impact of patents [36-37]. From the results in the figure, it can be observed that the yellow and green clusters are closely connected, indicating a strong link between DL technological advances and their application in patent analysis. The blue cluster is relatively independent, suggesting that the legal discussion around AID-IP forms a distinct research area.

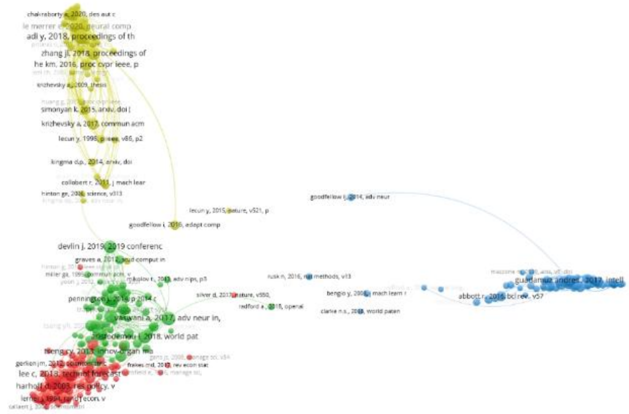

Fig. 6. Co-citation network.

C. Thematic Analysis

Fig. 7 gives the results of the word cloud visualization, visualizing the most common terms associated with AID-IP research. The size and coarseness of each term indicates its prominence in the research literature. It can be noticed that ‘Artificial Intelligence’ is the main keyword, and ‘Machine Learning’ and ‘Deep Learning’ occupy a prominent position, reflecting the key role of these technologies in AI research. ‘Copyright’, ‘Copyright Law’ and ‘Copyright Protection’ highlight the role of AI in copyright management, originality detection, and plagiarism detection. ‘Natural Language Processing’ emphasizes the impact of AI on text processing, information retrieval, and legal document analysis. ‘Generative AI’ demonstrates the growing concern about ownership, authorship, and copyright enforcement of works generated by AI.

Fig. 7. Word cloud.

In addition, ”Blockchain”, “Data Mining”, “BERT”, and “Transformer” appear in the word cloud, revealing the growing intersection between advanced AI technologies and IP protection. “Patent Classification” and “Patent Protection” shows that AI is being widely used to automate patent analysis, detect infringement, and improve the efficiency of patent searches.

Word clouds exemplify different intersections between DL and IP. The first is the role of AI in IP management, including DL model-driven patent classification, infringement detection, and copyright management, as well as automated systems for analyzing large-scale patent and legal documents. Second, embodying AIGC's legal and ethical challenges focuses on copyright issues, including how AI impacts innovation, creativity, and plagiarism detection. Finally, the word cloud also reflects emerging technologies for IP protection, such as NLP tools for contract analysis and legal text processing, and blockchain technology for ensuring IP transparency and security.

Principal Component Analysis (PCA) is used to reduce the dimensionality of the dataset while retaining the most important variance in the data [38]. The graph plots keywords in AID-IP research based on their similarity and co-occurrence patterns, with different clusters representing different topic areas.

The PCA diagram given in Fig. 8 reveals the different research themes in the field that are independent but interrelated, centered on AI and legal frameworks. The red cluster ("Artificial Intelligence," "patents and inventions," "copyright law,") represents research on AI-driven patent analysis, copyright protection, and legal aspects of AIGC. This cluster has far-reaching implications for policy development, legal revisions, and business models, and thus tends to be at the center of citations and discussions. The green cluster ("Natural Language Processing," "BERT," "patent classifications," "plagiarism detection,") focuses on research on NLP applications in patent classification, plagiarism detection, and document retrieval. Due to the mature application of NLP in patent text analysis, it has been recognized by academia and industry earlier, and the related results are more concentrated. The blue cluster ("watermarking," "intellectual property protection," "privacy protection,") focuses on cyber security, AI privacy and copyright infringement protection. The purple cluster ("convolutional neural networks," "patent infringements,") represents DL methods used in patent analysis, infringement detection, and automation. The orange cluster ("neural network models", "protection methods"), on the other hand, focuses on the use of DL to protect AI models and intellectual property. The research in the last three clusters is biased toward more specific technology implementations and application scenarios.

The five clusters in the figure are centered on legal frameworks and AI technologies, with discussions at the macro legal and policy levels (e.g. copyright, patent law, infringement issues, etc.), as well as research at the micro technology implementation level (e.g. NLP, CNN, watermarking technology, model protection, etc.). This phenomenon reflects that in the intersection of DL and IP, "legal compliance" and "technological innovation" have always been two parallel and intertwined threads. However, despite the multiple themes of "law", "AI algorithms" and "patent analysis" shown in the figure, the real interdisciplinary integration has yet to be further deepened. At present, most of the literature still remains in the static comparison or general discussion of laws and regulations and AI technology, and there is a relative lack of empirical research on specific judicial practices and business operation models. In addition, IP protection also involves economic incentives, ethical norms and social impacts, and related studies have not formed independent clusters in this figure, indicating that the multidimensional crossover in this field still needs to be expanded [39]. From the keywords of each cluster in the figure, it can be seen that the research mostly focuses on the level of technical prototypes (watermarking, model protection) or legal theories (copyright law, patent law), and there is a relative lack of discussion on the practical effects and policy evaluation, such as the case study of AIGC in judicial practice, and the criteria for the adoption of AI evidence in patent litigation.

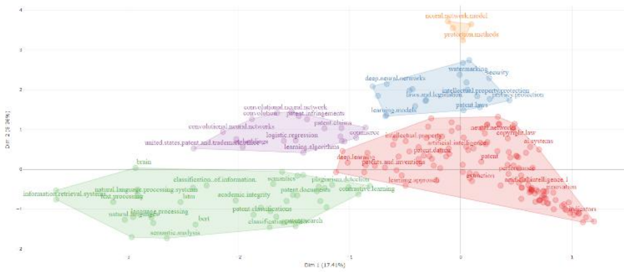

Fig. 8. Principal component analysis.

IV. Discussion

This section will address the research questions posed in the introduction based on the bibliometric analysis results of the experimental dataset.

Q1: Over the past decade, what has been the trend in the number of publications, citation patterns, and core journals in AID-IP research? Can the evolution of these themes reveal emerging IP challenges in the context of AI era?

AID-IP research has shown a significant growth trend over the past decade, with the number of documents increasing from 6 articles in 2015 to 192 in 2024, with an annual growth rate of 15.34 per cent. The citation trend shows that 2018 is the peak year of high citations, indicating that the research in this period has had a profound impact on subsequent work, such as the application of DL in patent classification and IP protection. Meanwhile, core journals such as World Patent Information and Journal of Intellectual Property Law & Practice have become important dissemination platforms in the field, reflecting the distinctive characteristics of interdisciplinary research.

The thematic evolution path shows that the research hotspots have gradually expanded from the early focus on IP protection of DL models (e.g. watermarking technology) to intelligent classification of patented text, technology prediction, and legal challenges of AIGC. This evolution reveals emerging IP challenges arising from the rapid development of AI technologies. AIGC has been increasingly discussed in recent studies, but its legal framework is not yet mature [40]. For example, research on DNN watermarking technology provides technical security for model attribution rights, but still needs to deal with the diversity and complexity of model misappropriation [41]. DL significantly improves the efficiency of patent categorization and trend prediction, but it also raises the issue of the patent system's adaptability to technological changes. Overall, the shifting theme of the literature suggests that technological innovation is driving the upgrading of protection tools, but it also reveals the lagging problem of existing IP laws and regulatory mechanisms. Despite the gradual shift of research hotspots to emerging issues, there are still fewer studies on the adaptation of AIGC and patent legal frameworks, especially the lack of empirical studies on the impact on judicial practice.

Q2: What differences can be observed in the contributions of different countries or regions to AID-IP research, based on geographic distribution and collaboration network data? What implications do these differences have for global IP protection strategies?

Bibliometric data shows that China and the United States dominate AID-IP research, reflecting their technological superiority and high priority in the field of AI. India comes third as an emerging contributor. European countries (e.g. Germany, UK, France) form a close regional cooperation network, while many developing countries (e.g. Latin America, parts of Africa) are less involved, and the research activities show a clear imbalance. Among the cooperative networks, China and the United States, as the central hubs of the global network, maintain close cooperation with several countries. Europe has close intra-regional collaboration but relatively little cross-regional collaboration. Emerging AI research countries such as India and South Korea are gradually integrating into the global collaborative network, but their research impact is still predominantly regional.

The dominance of China and the United States reflects their leadership in AI research investment, technology accumulation and resource reserves. Europe's close cooperation benefits from a unified IP framework and policy collaboration. However, international research and cooperation also highlights the marginalization of developing countries in AID-IP research. The regional concentration of research activities reflects global imbalances in resource allocation, talent pool and technology base. While regional cooperation can promote standardization in local areas, in the context of globalization, it is difficult to directly translate the technical or policy advantages of a single region into a global consensus. In the future, there is a need to strengthen cross-regional cooperation, especially to support the integration of developing countries into global research networks and to narrow the gap between technical and legal capabilities. With the global proliferation of AI technology, more uniform and inclusive IP protection rules need to be established at the international level. On the basis of respecting the legal and technological differences among countries, regional cooperation should be promoted to transform into globalization.

Q3: In the context of the AI era, what specific areas does DL technology cover in IP applications? What are the most prominent challenges in each subfield?

DL technology in the IP field primarily covers subfields such as digital copyright protection [42], patent classification and retrieval [43], trademark and brand evaluation [44], and technological innovation forecasting [45]. Table V lists key applications in each subfield, the commonly used DL models, and the main challenges currently faced in each area.

Currently, although DL technology has covered a number of IP application areas, the depth of research on specific areas varies, especially the empirical research related to AIGC and patent infringement is relatively small. Some of the hotspots (e.g., model protection technology) are more maturely researched, but no systematic solution has been developed for emerging issues (e.g., legal attribution of AIGC). The rapid development of DL technology has exceeded the adaptability of the existing legal framework, and the research needs to establish a closer linkage between the technology and the law.

TABLE V. KEY CHALLENGES AND COMMON MODELS FOR DL-BASED IP APPLICATIONS

IP Field	Key Challenges	DL Models	Key Applications
Patent Classification and Retrieval	- Complex text classification - Cross-lingual search	BERT, Siamese Network, FAISS	- Automatic classification - Intelligent retrieval - Patent trend analysis
Digital Copyright Protection	- Difficulty in infringement detection - Tracing AIGC	CNN, ViT, GAN, CLIP	- Infringement detection - DeepFake recognition - Digital watermarking
Trademark and Brand Evaluation	- Identifying similar trademarks - Detecting forgeries	ResNet, GAN, DETR	- Trademark similarity detection - Counterfeit identification
Technology Innovation Forecasting	- Challenges in predicting future trends	LSTM, CNN, XGBoost	- Patent valuation - Technology trend forecasting

Q4: Based on the thematic analysis results, is there a gap in the literature regarding the application of DL technology in IP protection and its discussion within the context of IP laws and policy frameworks? What theoretical or practical shortcomings does this gap reflect? How should future research break through existing theoretical frameworks to better address the needs of technological development and legal regulation?

The thematic analysis shows that the literature mainly focuses on the application of DL technology itself (e.g. watermarking technology, patent classification, infringement detection), while there is less discussion of IP legal and policy frameworks. A certain degree of short layer does exist between the two. Firstly, there is a disconnect between technology and law; research on DL technology mostly stays at the level of theory and methodology, while there is less research on its legal applicability and judicial practice. Secondly, there is a lag between policy and application; issues such as attribution of AIGC products and infringement determination have become hotspots, but the adjustment and adaptation of relevant laws and policies have not yet kept pace with the development of the technology. Finally, interdisciplinary integration is still insufficient. In the past, the discussion of technical issues and legal frameworks in research was mostly independent research, lacking interdisciplinary integration in practical application scenarios.

This disconnection reflects the singular technological orientation of current research, which makes it difficult for the academic community to comprehensively assess the social costs and legal liability risks that may arise from the diffusion of the technology. Merely pursuing technological innovation while neglecting the legal, ethical and regulatory research that goes with it may lead to unforeseen problems in practical application, ultimately affecting the sustainable development of the technology. In the future, it is necessary to strengthen the integration of technology and law from both theoretical and practical dimensions to promote the practical application of DL technology in IP protection.

Future research should start from both macro (legal framework and policy coordination) and micro (technology realization and practical application) levels. Firstly, through technological innovation, explore more efficient DL model protection techniques, such as traceability mechanisms combined with blockchain or more secure model encryption methods. Second, study the applicability of DL technology in different judicial systems and promote the coordination and harmonization of transnational legal frameworks. In terms of interdisciplinary cooperation, it should strengthen the in-depth integration of law, policy and technology fields, and promote empirical research and case analysis. Finally, it should also focus on the social impact of DL technology in IP protection, especially on industrial innovation, personal privacy and legal fairness.

V. Conclusion

This study systematically analyzes the current research status and development trend of AID-IP field over the past decade. From the overall perspective of bibliometrics, AID-IP research has shown significant growth in the past decade, with the number of documents, citation trends and core journal distribution reflecting a high degree of academic interest in this field. The analysis of thematic evolution shows a gradual transition from single technology optimization to research at the intersection of technology and law and policy, but there is still a clear disconnect in interdisciplinary collaboration, theoretical integration and policy response. Differences in geographic distribution and international cooperation further reveal the uneven investment in technology and application in different regions, suggesting that global IP protection strategies urgently need to be more coordinated in terms of standard-setting and transnational regulation. In addition, compared with traditional methods, DL-based IP protection technologies have obvious advantages in terms of robustness and automation level, but systematic discussions on their potential risks and legal gray areas are still insufficient, and innovative research integrating technological and legal issues has not yet gained sufficient attention, which should further promote the organic integration of technological innovation and legal regulation in the future through cross-disciplinary cooperation and the establishment of new theoretical frameworks. Despite the contributions of this study, certain limitations should be acknowledged. The bibliometric analysis is based solely on data from two major academic databases—Scopus and WoSCC—which may not fully capture the breadth and diversity of research outputs in this domain. Future studies could expand the scope by incorporating additional data sources to provide a more comprehensive and inclusive understanding of the AID-IP research landscape.

Acknowledgment

This research was supported by the Henan Provincial Research-Based Teaching Reform and Practice Project (Project No. Jiao Gao [2023]388-33) and the Higher Education Teaching Reform Project of Henan University of Science and Technology (Project No. 2024BK042). We gratefully acknowledge this institutional support. We also sincerely thank the editorial team and anonymous reviewers for their valuable comments and suggestions.

References

[1] D. K. Sharma and N. F. Ipr, “INTELLECTUAL PROPERTY AND THE NEED TO PROTECT IT,” Indian J.Sci.Res, Jan. 2014, [Online]. Available: https://www.researchgate.net/profile/Dushyant_Sharma/publication/267039883_INTELLECTUAL_PROPERTY_AND_THE_NEED_TO_PROTECT_IT/links/5443bc010cf2a76a3ccd669b.pdf

[2] P. Kadian, S. M. Arora, and N. Arora, “Robust Digital Watermarking Techniques for Copyright Protection of Digital Data: A survey,” Wireless Personal Communications, vol. 118, no. 4, pp. 3225–3249, Feb. 2021, doi: 10.1007/s11277-021-08177-w.

[3] W. Yang, “Legal Regulation of Intellectual Property Rights in the Digital Age: A Perspective from AIGC Infringement,” Science of Law Journal, vol. 3, no. 3, Jan. 2024, doi: 10.23977/law.2024.030322.

[4] T. Šarčević, A. Karlowicz, R. Mayer, R. Baeza-Yates, and A. Rauber, “U can’t gen this? A survey of Intellectual Property Protection Methods for Data in Generative AI,” arXiv (Cornell University), Apr. 2024, doi: 10.48550/arxiv.2406.15386.

[5] L. Chen, S. Xu, L. Zhu, J. Zhang, X. Lei, and G. Yang, “A deep learning based method for extracting semantic information from patent documents,” Scientometrics, vol. 125, no. 1, pp. 289–312, Jul. 2020, doi: 10.1007/s11192-020-03634-y.

[6] Q. Fang, “Designing of music copyright protection system based on deep belief network and blockchain,” Soft Computing, vol. 28, no. 2, pp. 1669–1684, Dec. 2023, doi: 10.1007/s00500-023-09515-9.

[7] X. Lin, “Copyright protection and risk assessment based on information extraction and machine learning: the case of online literary works,” Scalable Computing Practice and Experience, vol. 25, no. 5, pp. 3822–3831, Aug. 2024, doi: 10.12694/scpe.v25i5.3002.

[8] H. Alshowaish, Y. Al-Ohali, and A. Al-Nafjan, “Trademark image similarity detection using convolutional neural network,” Applied Sciences, vol. 12, no. 3, p. 1752, Feb. 2022, doi: 10.3390/app12031752.

[9] B. D. Rouhani, H. Chen, and F. Koushanfar, “DeepSigns,” arXiv, Apr. 2019, doi: 10.1145/3297858.3304051.

[10] H. Jiang, S. Fan, N. Zhang, and B. Zhu, “Deep learning for predicting patent application outcome: The fusion of text and network embeddings,” Journal of Informetrics, vol. 17, no. 2, p. 101402, Mar. 2023, doi: 10.1016/j.joi.2023.101402.

[11] Z. Li et al., “ERIC-UP^3 Benchmark: E-Commerce Risk Intelligence classifier for detecting infringements based on utility patent and product pairs,” OpenReview. https://openreview.net/forum?id=4oj7tYujwP

[12] M. Z. Choksi and D. Goedicke, “Whose text is it anyway? Exploring BigCode, intellectual property, and ethics,” arXiv (Cornell University), Jan. 2023, doi: 10.48550/arxiv.2304.02839.

[13] Z. Wang, C. Chen, V. Sehwag, M. Pan, and L. Lyu, “Evaluating and mitigating IP infringement in visual Generative AI,” arXiv (Cornell University), Jun. 2024, doi: 10.48550/arxiv.2406.04662.

[14] J. Drexl et al., “Technical Aspects of Artificial Intelligence: An Understanding from an Intellectual Property Perspective,” SSRN Electronic Journal, Jan. 2019, doi: 10.2139/ssrn.3465577.

[15] A. Caputo and M. Kargina, “A user-friendly method to merge Scopus and Web of Science data during bibliometric analysis,” Journal of Marketing Analytics, vol. 10, no. 1, pp. 82–88, Oct. 2021, doi: 10.1057/s41270-021-00142-7.

[16] M. Aria and C. Cuccurullo, “bibliometrix : An R-tool for comprehensive science mapping analysis,” Journal of Informetrics, vol. 11, no. 4, pp. 959–975, Sep. 2017, doi: 10.1016/j.joi.2017.08.007.

[17] S. Li, J. Hu, Y. Cui, and J. Hu, “DeepPatent: patent classification with convolutional neural networks and word embedding,” Scientometrics, vol. 117, no. 2, pp. 721–744, Sep. 2018, doi: 10.1007/s11192-018-2905-5.

[18] J.-S. Lee and J. Hsiang, “Patent classification by fine-tuning BERT language model,” World Patent Information, vol. 61, p. 101965, Jun. 2020, doi: 10.1016/j.wpi.2020.101965.

[19] J. Zhang et al., Protecting Intellectual Property of Deep Neural Networks with Watermarking. 2018, pp. 159–172. doi: 10.1145/3196494.3196550.

[20] Z. Li, C. Hu, Y. Zhang, and S. Guo, How to prove your model belongs to you. 2019. doi: 10.1145/3359789.3359801.

[21] X. Cao, J. Jia, and N. Z. Gong, IPGUARD: Protecting intellectual property of deep neural networks via fingerprinting the classification boundary. 2021. doi: 10.1145/3433210.3437526.

[22] A. Levendowski, "How copyright law can fix artificial intelligence's implicit bias problem," Washington Law Review, vol. 93, no. 2, p. 579, Jun. 2018, [Online]. Available: https://digitalcommons.law.uw.edu/cgi/viewcontent.cgi?article=5042&context=wlr

[23] B. Lee, O. Kwon, M. Kim, and D. Kwon, "Early identification of emerging technologies: A machine learning approach using multiple patent indicators," Technological Forecasting and Social Change, vol. 127, pp. 291–303, Nov. 2017, doi: 10.1016/j.techfore.2017.10.002.

[24] S. Woo, P. Jang, and Y. Kim, "Effects of intellectual property rights and patented knowledge in innovation and industry value added: A multinational empirical analysis of different industries," Technovation, vol. 43–44, pp. 49–63, Apr. 2015, doi: 10.1016/j.technovation.2015.03.003.

[25] H. Fujii and S. Managi, "Trends and priority shifts in artificial intelligence technology invention: A global patent analysis," Economic Analysis and Policy, vol. 58, pp. 60–69, Jan. 2018, doi: 10.1016/j.eap.2017.12.006.

[26] R. Chikkamath, V. R. Parmar, C. Hewel, and M. Endres, "Patent Sentiment Analysis to highlight patent paragraphs," arXiv (Cornell University), Jan. 2021, doi: 10.48550/arxiv.2111.09741.

[27] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks," Neural Information Processing Systems, vol. 25, pp. 1097–1105, Dec. 2012, [Online]. Available: http://books.nips.cc/papers/files/nips25/NIPS2012_0534.pdf

[28] Y. Lecun, L. Bottou, Y. Bengio, and P. Haffner, "Gradient-based learning applied to document recognition," Proceedings of the IEEE, vol. 86, no. 11, pp. 2278–2324, Jan. 1998, doi: 10.1109/5.726791.

[29] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," Nature, vol. 521, no. 7553, pp. 436–444, May 2015, doi: 10.1038/nature14539.

[30] Goodfellow, Y. Bengio, and A. Courville, Deep learning. 2016. [Online]. Available: https://dl.acm.org/citation.cfm?id=3086952

[31] Devlin, M.-W. Chang, K. Lee, and K. Toutanova, BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. 2019. doi: 10.18653/v1/n19-1423.

[32] A.Vaswani et al., "Attention is All you Need," arXiv (Cornell University), vol. 30, pp. 5998–6008, Jun. 2017, [Online]. Available: https://arxiv.org/pdf/1706.03762v5

[33] Aristodemou and F. Tietze, "The state-of-the-art on Intellectual Property Analytics (IPA): A literature review on artificial intelligence, machine learning and deep learning methods for analysing intellectual property (IP) data," World Patent Information, vol. 55, pp. 37–51, Oct. 2018, doi: 10.1016/j.wpi.2018.07.002.

[34] R. Abbott, "I think, therefore I invent: creative computers and the future of patent law," SSRN Electronic Journal, Jan. 2016, doi: 10.2139/ssrn.2727884.

[35] A. Guadamuz, "Do androids dream of electric copyright? Comparative analysis of originality in artificial intelligence generated works," SSRN Electronic Journal, Apr. 2017, doi: 10.17605/osf.io/v9nzb.

[36] C.-Y. Tseng and P.-H. Ting, "Patent analysis for technology development of artificial intelligence: A country-level comparative study," Innovation, vol. 15, no. 4, pp. 463–475, Dec. 2013, doi: 10.5172/impp.2013.15.4.463.

[37] D. Harhoff, F. M. Scherer, and K. Vopel, "Citations, family size, opposition and the value of patent rights," Research Policy, vol. 32, no. 8, pp. 1343–1363, Dec. 2002, doi: 10.1016/s0048-7333(02)00124-5.

[38] N. Gaur, R. Chaudhary, M. Yadav, S. Srivastava, V. Chaudhary, and M. A. Shah, "A stochastic analysis and bibliometric analysis of COVID-19," Indian Journal of Microbiology Research, vol. 11, no. 4, pp. 342–353, Dec. 2024, doi: 10.18231/j.ijmr.2024.058.

[39] J. J. Osei-Tutu, "Socially Responsible Corporate IP," Vanderbilt Journal of Entertainment & Technology Law, vol. 21, no. 2, pp. 483–516, Jan. 2018, [Online]. Available: https://ecollections.law.fiu.edu/cgi/viewcontent.cgi?article=1393&context=faculty_publications

[40] G. Xuan, "Risks and regulatory framework of AI-Generated Content (AIGC) in the judicial field," Journal of Education Humanities and Social Sciences, vol. 19, pp. 278–282, Aug. 2023, doi: 10.54097/ehss.v19i.11144.

[41] X. Zhuang, L. Zhang, C. Tang, and Y. Li, "DEEPREG: a trustworthy and Privacy-Friendly ownership regulatory framework for deep learning models," IEEE Transactions on Information Forensics and Security, p. 1, Jan. 2024, doi: 10.1109/tifs.2024.3518061.

[42] T. Rajput and B. Arora, "A Systematic review of deepfake detection using learning Techniques and Vision Transformer," Lecture Notes in Networks and Systems, pp. 217–235, Jan. 2024, doi: 10.1007/978-981-97-2550-2_17.

[43] H. Bekamiri, D. S. Hain, and R. Jurowetzki, "PatentSBERTa: A deep NLP based hybrid model for patent distance and classification using augmented SBERT," Technological Forecasting and Social Change, vol. 206, p. 123536, Jun. 2024, doi: 10.1016/j.techfore.2024.123536.

[44] D. Vesnin, D. Levshun, and A. Chechulin, "Trademark similarity evaluation using a combination of VIT and local features," Information, vol. 14, no. 7, p. 398, Jul. 2023, doi: 10.3390/info14070398.

[45] Y. Zhou, F. Dong, Y. Liu, Z. Li, J. Du, and L. Zhang, "Forecasting emerging technologies using data augmentation and deep learning," Scientometrics, vol. 123, no. 1, pp. 1–29, Jan. 2020, doi: 10.1007/s11192-020-03351-6.