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The Climate of Innovation: AI's Growing Influence in Weather Prediction Patents and Its Future Prospects

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Abstract: As the severity of climate change intensifies, understanding and predicting weather patterns have become paramount. Major firms worldwide have recognized this urgency, focusing their innovative efforts on weather prediction. In line with this trend, this research delves into the intricate patterns of patent data within the realm of weather prediction from 2010 to 2023. The study unveils a standard timeline for patent grants in this domain, particularly noting a distinctive peak in grant durations between 1500 and 2000 days. The global landscape of weather prediction innovation is highlighted, pinpointing the United States, China, and Japan as pivotal contributors. A salient finding is the ascendant influence of artificial intelligence (AI) in this sector, underscored by the prevalence of AI-centric keywords such as "machine learning" and "neural network". This trend exemplifies the ongoing paradigm shift toward data-driven methodologies in weather forecasting. A notable correlation was identified between patent trends and academic trends on platforms such as arXiv, especially concerning keywords such as "machine learning" and "deep learning". Moreover, our findings indicate that the transformer network, given its rising prominence in deep learning realms, is predicted to be a future keyword trend in weather prediction patents. However, despite its insights, the study also grapples with limitations in its predictive modeling component, which aims at forecasting patent grant durations. Overall, this research offers a comprehensive understanding of the patent dynamics in weather prediction, illuminating the trajectory of technological advancements and the burgeoning role of AI. It holds implications for academia, industry, and policymaking in navigating the future of weather prediction technologies.

Keywords: artificial intelligence; data-driven approaches; patent analysis; text mining; weather prediction

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1. Introduction

Weather prediction has long been a cornerstone of our ability to understand and adapt to the ever-changing dynamics of our environment [1]. As the global climate continues to undergo profound shifts, the importance of accurate and timely weather forecasting has never been more apparent [2]. The consequences of climate change, including extreme weather events, rising temperatures, and shifting precipitation patterns, underscore the critical need for reliable weather prediction systems that can help us mitigate risks, protect lives, and safeguard vital resources [3,4].

In recent years, the intersection of meteorology and technology has ushered in a new era of weather prediction. Advanced computational models, satellite imaging, and data analytics have revolutionized our ability to anticipate and respond to weather-related challenges [5]. Modern numerical weather prediction (NWP) has its roots in the 1920s [6]. Yet, with the emergence of data-driven techniques, especially deep learning models, we have not only reduced computational demands but also maintained or even improved the accuracy of predictions in comparison with traditional NWP methodologies [7]. This

transformation has not only improved our understanding of atmospheric processes but has also paved the way for innovative solutions that can help us navigate an increasingly unpredictable climate.

The graph in Figure 1 illustrates the projected growth of the weather forecasting service market from 2022 to 2032. The market size, measured in billions of USD, is seen to exhibit a consistent upward trajectory over the decade. Starting at 1.9 billion in 2022, it is projected to soar to 4.6 billion by 2032 [8]. This steady increase underscores the escalating significance and investments directed toward weather forecasting services. The rise can be attributed not only to traditional methods but also to the increasing application of advanced technologies in the field. Leading tech giants such as Google, NVIDIA, and Microsoft have ventured into this domain, leveraging deep learning models to revolutionize weather forecasting [9–11]. Such initiatives from major corporations validate the importance of weather prediction in today's age and showcase the immense potential of combining meteorology with cutting-edge technology.

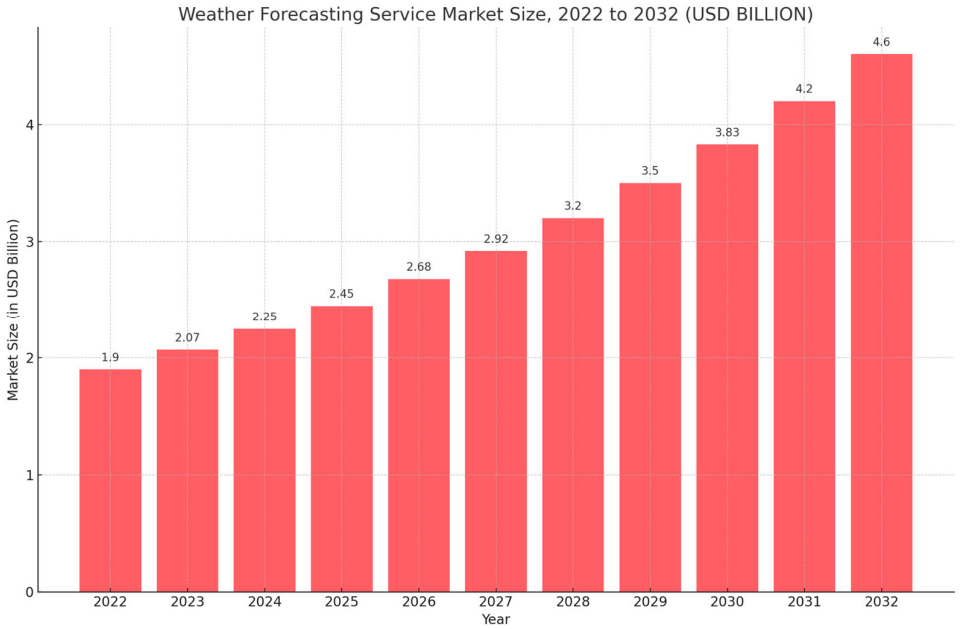


Figure 1. Accelerating Growth of the Weather Forecasting Service Market (2022–2032).

Within this dynamic landscape, the patenting of weather prediction technologies has emerged as a key indicator of innovation and progress. Patents not only serve as a testament to human ingenuity but also play a pivotal role in the dissemination and commercialization of cutting-edge weather forecasting methodologies and tools [12]. Analyzing patent data within the field of weather prediction is thus a valuable endeavor, as depicted in Figure 1, which illustrates the accelerating growth of the weather forecasting service market (2022–2032). This graph is justified by its relevance in highlighting the market's rapid expansion, reflecting the increased investment and commercialization of cutting-edge weather forecasting methodologies and tools.

The primary objective of this paper is to conduct a comprehensive analysis of patent data within the field of weather prediction. By exploring patent grant durations, the geographical distribution of innovations, emerging technologies such as the "transformer" model, and keyword trends, this study seeks to provide valuable knowledge that could unlock crucial insights into the dynamics of innovation in a weather prediction domain that directly impacts society. Two different approaches, including trend analysis with text mining and predicting patent grant duration through machine learning algorithms, were utilized during the experiments.

Moreover, to complement our understanding and ensure a more holistic view, we integrated datasets from arXiv. arXiv, renowned for its rich repository of AI-related papers,

provides an invaluable context to our study [13]. By incorporating scholarly articles from arXiv, we could juxtapose our patent trends against a backdrop of cutting-edge academic discourse, especially in artificial intelligence.

By shedding light on the burgeoning role of artificial intelligence, showcasing predictive modeling possibilities for patent grant durations, and identifying future research directions, this paper contributes to bridging gaps in patent analysis. Ultimately, the research carries significance in its potential to drive innovation and enhance our capacity to address real-world weather-related challenges, thus benefiting both scientific advancements and society at large.

2. Literature Review

Numerous studies have delved into discerning patent trends using text-mining techniques. In this section, we begin by exploring the methodologies of these experiments, shedding light on their primary findings and outcomes. Additionally, we will also address various papers focusing on weather prediction within this discussion.

Rezende et al. presented a data-mining framework for patents by leveraging natural language processing. This technique focuses on analyzing technological trends and comparing patent similarities. Using the US Patent and Trademark Office's data, a decline in flash memory and PDA technologies was observed from 2010 to 2018. Furthermore, to determine patent similarity, methods such as LSA, Word2vec, and WMD were compared with the Jaccard index. LSA and WMD showed comparable results, whereas Jaccard's indications differed from the aforementioned methods [14]. Gim et al., introduced a trend analysis method, leveraging ETI relations to discern patterns from patent datasets. Results from a real IoT patent dataset revealed 98.6% expansion relations and 1.4% transition relations among ETI relations. The study also confirms that proposed dictionaries enhance accuracy in extracting ETI relations from patent networks automatically [15]. Han et al. developed a unique interactive method, PatStream, for analyzing patent dataset trends. This system integrates multiple views linked by brushing and offers a streamgraph view for spotting technological trends. Additional views present deeper insights such as IPC distribution, patent applicants, and innovation scores. Backed by advanced natural language processing, PatStream aids in concept extraction and patent similarity evaluations. A use case from the "inductive sensor" field demonstrated PatStream's efficiency in giving a quick technology overview and aiding in technology management decisions [16].

Hotte and Jee devised a framework that combines patent analysis and Twitter data mining to monitor emerging technologies. The research involved tracking the technology's evolution through patents and gauging Twitter users' perceptions and expectations about it. By comparing results from both data sources, CCATs demonstrated strong technological complementarities with mitigation, as over 25% of CCATs offer mitigation benefits, and this result offers insights into the development trends of the technology [17]. Touboul et al. examined global innovation rates in climate adaptation technology, spotlighting leading nations and technology diffusion patterns. The findings indicate slower progress in adaptation technology innovation compared with low-carbon technologies since 2005, especially in slower-innovating sectors such as agriculture. A significant portion of this innovation is centralized in China, Germany, Japan, South Korea, and the U.S., which make up almost two-thirds of global patented inventions for climate adaptation. Notably, technology transfer through patents is minimal, particularly in areas such as agriculture and flood protection, with negligible transfers to low-income countries. This creates a prominent disparity between countries' adaptation necessities and the available technological solutions [18].

Distinct from the aforementioned studies, our work diverges in two critical ways. Firstly, we narrow our focus to specific AI technologies within patents related to weather prediction. Secondly, we delve deeper into assessing the influence of AI-related keywords on the duration it takes for a patent to be granted. This specialized approach sets our research apart from those related works previously introduced.

3. Materials and Methods

3.1. Data Description and Preprocessing

In the course of our research, we collected datasets from two renowned platforms: arXiv and Google Patents. From arXiv, using the API, we extracted a dataset of 10,000 scholarly articles associated with "weather prediction", ensuring a diverse and comprehensive collection that reflects the current academic discourse in weather forecasting research. In parallel, we mined data from Google Patents, amassing 12,307 patents related to "weather prediction". The patents database was chosen for its extensive coverage, including all publicly disclosed patents, which offers a broad view of the technological advancements and innovation trends within the weather prediction domain. This extensive dataset collection from both academic articles and patents provides a robust foundation for our analysis, ensuring a thorough overview of advancements in weather prediction [19,20].

3.2. Exploratory Data Analysis (EDA)

The distribution in Figure 2 displayed a pronounced peak between 1500 and 2000 days (approximately 4 to 5.5 years) from the priority date, defined as the date when the patent application was first filed, to the grant date. This indicates that many weather prediction innovations experienced this specific duration for their patenting journey, suggesting a common timeline for many patents in this domain. Although the peak around 1500–2000 days was dominant, there were also patents that were granted in much shorter durations, as well as those that took considerably longer. This range demonstrates the varied nature of the patenting process, where some innovations might swiftly navigate the system, whereas others face extended scrutiny or challenges. The pronounced peak in the 1500–2000-day range suggests a standard timeline that many weather prediction innovations adhere to in their journey from priority to grant. This could be indicative of the typical complexities and challenges faced during the patent review process in this domain.

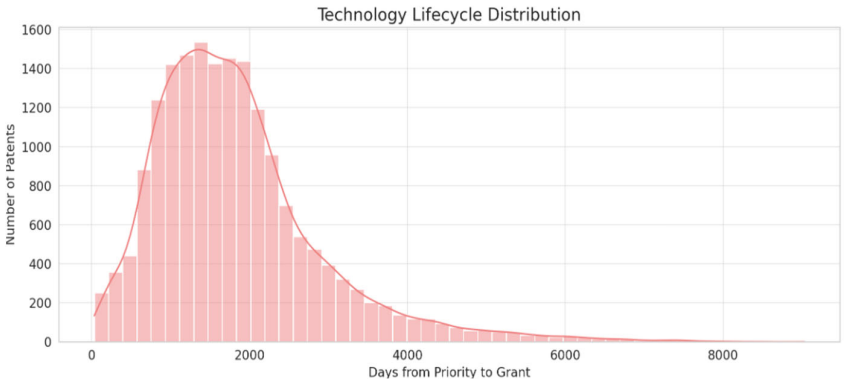


Figure 2. Visualization illustrating the distribution of technology lifecycles, measured by the duration in days between the initial priority date and the eventual grant of the patent.

From 2010 to 2023 there is a discernible upward trend in the number of patents granted each year. This steady growth underscores the sustained and increasing interest in weather prediction technologies. Although the growth has been consistent, the years 2020, 2021, and 2022 stand out as having a more pronounced increase in patent counts (Figure 3). These spikes could be indicative of major technological advancements, heightened research activities, or the emergence of novel prediction methodologies during these years [21].

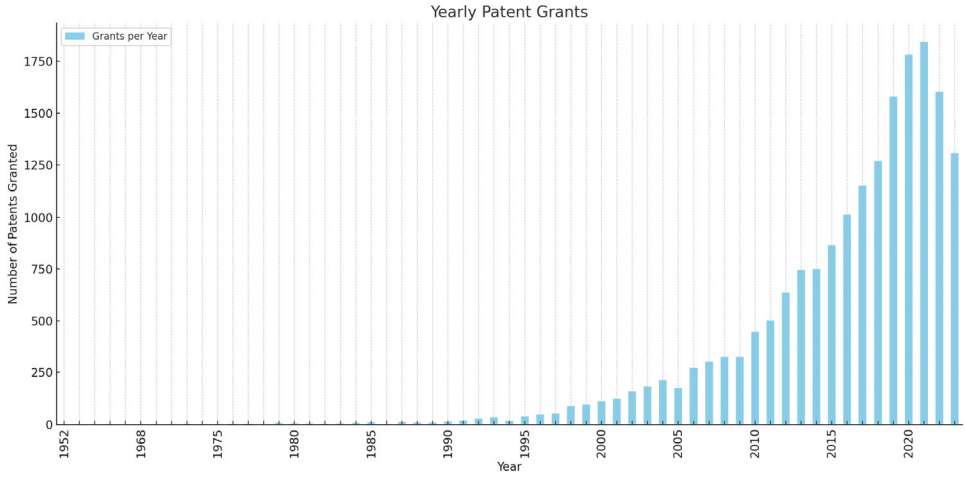


Figure 3. Bar graphs showcasing the annual progression of patent registrations, highlighting the growth trajectory of patent submissions year by year. Year 2023 shows a relatively lower number of patent grants, which can be attributed to the fact that our research was conducted in 2023 and the year had not yet concluded at the time of data collection. As a result, the data for 2023 may appear lower due to the incomplete year of patent grants in our dataset.

The dataset was predominantly characterized by patents from the United States, followed by China and Japan. This distribution in Figure 4 suggests that the United States is a significant hub of innovation, with China and Japan also playing major roles in global technological advancements regarding the fields of weather prediction.

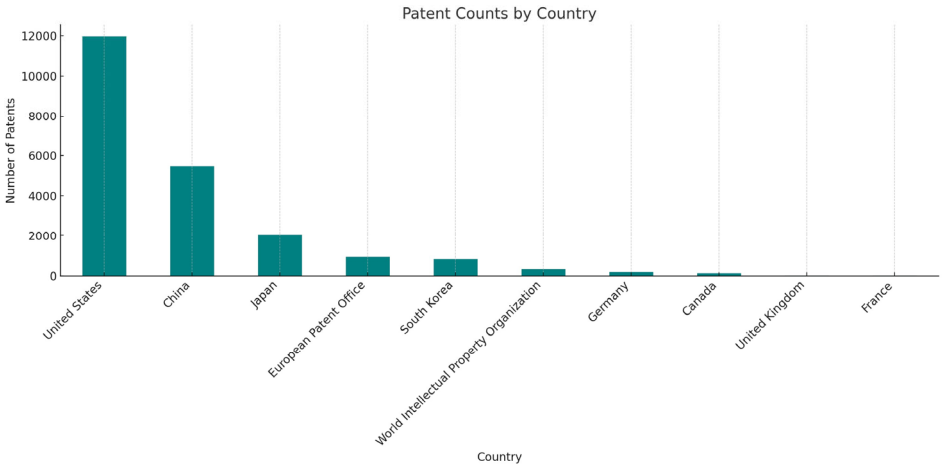


Figure 4. Comprehensive Analysis of Patent Registrations Categorized by Country of Origin.

Using patent data from 2010 to 2023, the present authors conducted a temporal keyword trend analysis on patent titles. By transforming titles into a bag-of-words representation with a focus on the most meaningful terms (excluding common stop words), we extracted and counted keyword occurrences using scikit-learn's CountVectorizer [22]. Figure 5 presents the yearly frequency of these top keywords, employing a distinct color palette (tab10 colormap) for clarity. The resulting line chart offers insights into the evolving technological focal points over the years, highlighting terms such as "apparatus", "based", "control", and the emerging emphasis on "prediction" in recent years that are potentially indicative of rising trends in predictive technologies.

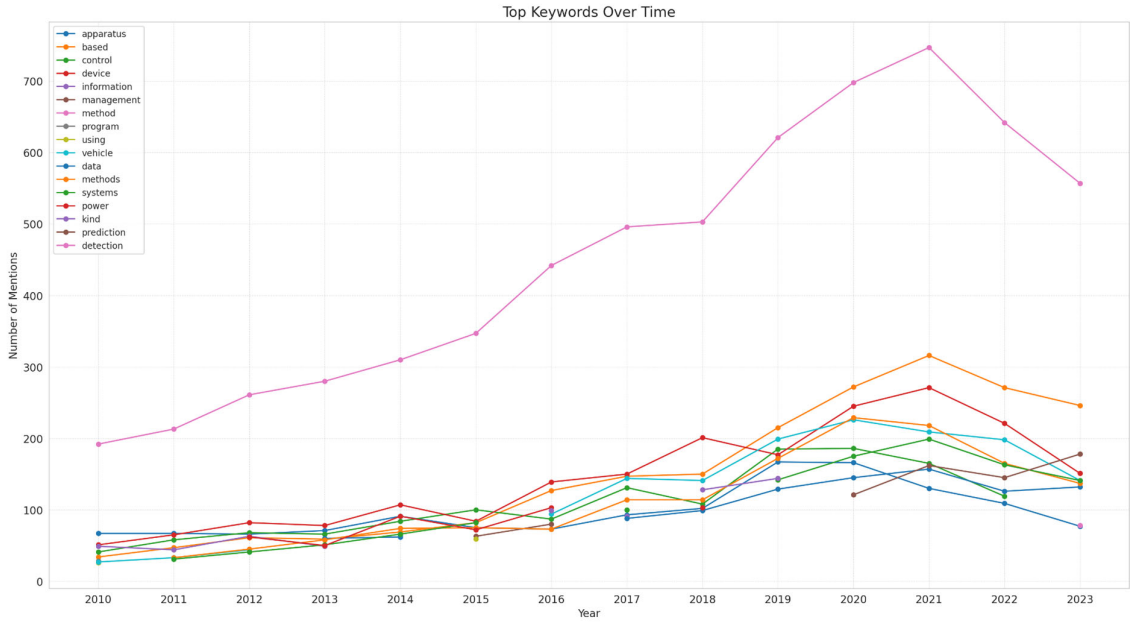


Figure 5. Temporal distribution of keywords related to weather prediction: an analysis based on a patent dataset. Year 2023 shows a relatively lower counts of those keywords, which can be attributed to the fact that our research was conducted in 2023 and the year had not yet concluded at the time of data collection. As a result, the data for 2023 may appear lower due to the incomplete year of patent grants in our dataset.

From the word clouds in Figure 6, we observed a noticeable emergence of keywords related to machine learning methodologies. The terms "machine learning" and "neural network" began to prominently appear from the year 2021 onwards. This suggests a growing trend in the adoption and application of machine learning techniques, especially neural networks, in the field of weather prediction.

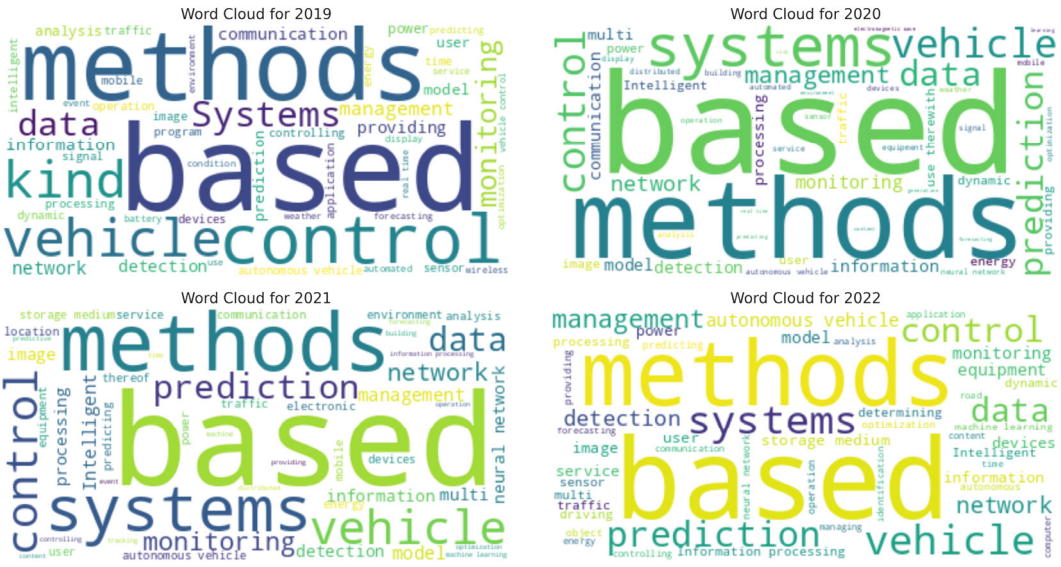


Figure 6. Word Cloud Visualization Depicting Keyword Trends from 2019 to 2022.

The prominence of these terms in more recent years indicates a potential paradigm shift. Whereas traditional methods have historically dominated the field of weather prediction, the rise of machine-learning- and neural-network-related patents suggests that these techniques are now being increasingly recognized for their potential to enhance predictive

accuracy and efficiency. This could reflect the broader trend in various scientific domains where data-driven methodologies are being adopted to address complex problems.

As evidenced by the word cloud results, "machine learning" and "neural network" have emerged as prominent keywords in patent titles. To delve deeper into this trend, we conducted a granular analysis focusing on three pivotal terms: "machine learning", "deep learning", and "artificial intelligence". Our findings depicted in Figure 7 indicate a rise in mentions of "machine learning" beginning in 2020, peaking in 2022, and then declining in 2023. In contrast, "deep learning" saw an upswing from 2019 to 2021, dipped in 2022, and then rebounded in 2023. Interestingly, the trend for "artificial intelligence" mirrored that of "machine learning", suggesting potential overlaps or synergies in their applications.

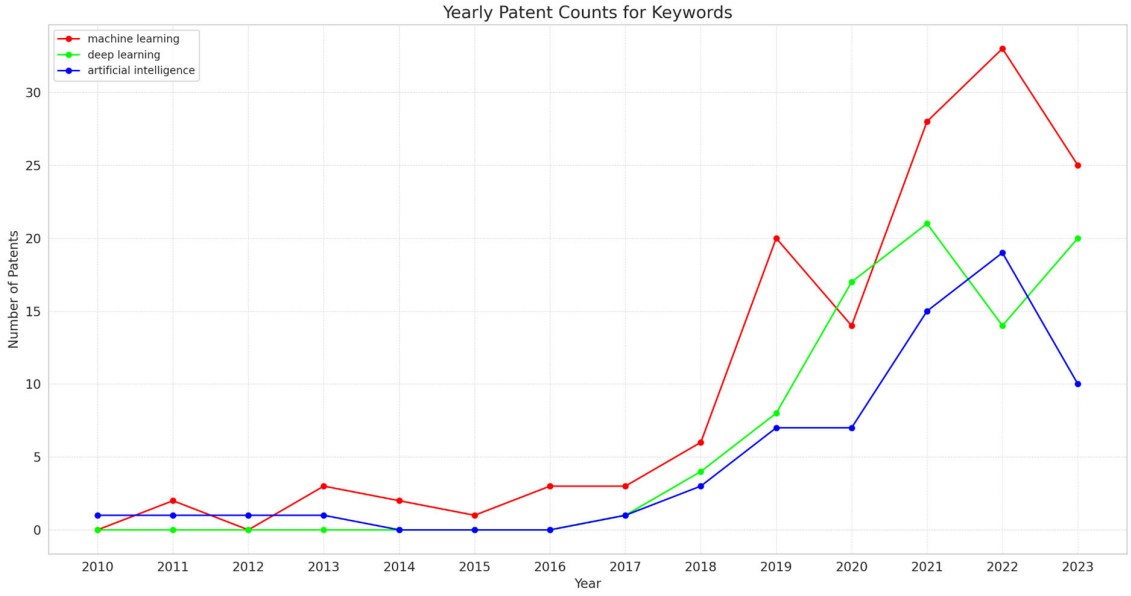


Figure 7. Comprehensive visualization illustrating the yearly trends in patent counts and highlighting three key technological domains: machine learning, deep learning, and artificial intelligence.

3.3. Light Gradient-Boosting Machine

Before delving into specific methodologies, it is essential to understand key AI concepts. One such concept is the light gradient-boosting machine (LightGBM), a gradient-boosting framework that employs tree-based algorithms that is optimized for speed and efficiency. Firstly, its histogram-based approach constructs histograms for continuous features, thereby reducing potential split points and accelerating the training process. Additionally, the introduction of gradient-based one-side sampling (GOSS) ensures efficient learning by prioritizing data instances with larger gradients. The exclusive feature bundling (EFB) technique groups exclusive features together, reducing data dimensionality and further enhancing efficiency. Furthermore, its leaf-wise tree-growth strategy offers better accuracy over conventional level-wise approaches [23,24].

3.4. Transformer

Within the rapidly evolving realm of deep learning, the "transformer" architecture stands out as a monumental advancement. Originally presented by Vaswani et al. in their 2017 paper "Attention Is All You Need", the transformer model eschews the recurrent or convolutional modules that were predominant in earlier sequence-to-sequence models. Instead, it is constructed around the self-attention mechanism, a feature that enables it to weigh the relevance of different parts of input data in relation to a particular item in the sequence. In the transformer's structure, both the encoder and decoder consist of a series of stacked identical layers. Each layer comprises two main components: a multi-head self-attention mechanism and a position-wise feed-forward network. The multi-head attention mechanism allows the model to focus on different positions in the input simultaneously,

capturing a diverse range of relationships and dependencies. The position-wise feed-forward network processes the output from the multi-head attention in parallel, enhancing transformation capabilities [25].

4. Result

Trend analysis was also conducted for certain keywords ("machine learning", "deep learning", and "transformer) with two different datasets from arXiv and Google Patent, which are exhibited in Figures 8–10. We calculated a Pearson correlation coefficient, which measures the linear relationship between datasets; a value close to 1 indicates a strong positive correlation. High correlation values (e.g., >0.9 for "machine learning" and "deep learning") between academic research (arXiv) and patent trends suggest synchronized advancements in both sectors. Such synchrony implies that technologies or methodologies represented by these keywords are mature, with academia and industry innovating concurrently. On the other hand, a moderate correlation (e.g., 0.5 for "transformer") might hint at a disparity between academic research and its industrial application.

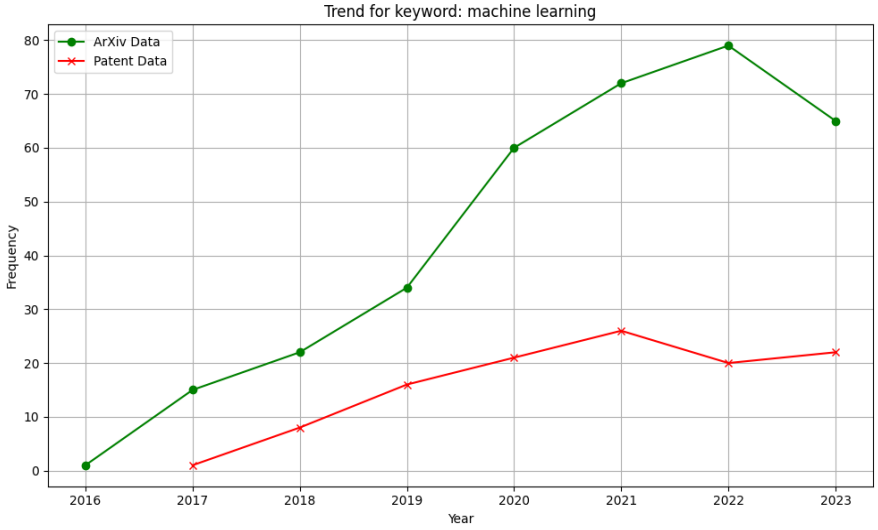


Figure 8. Visualization showcasing a comparative analysis of the yearly trend for the keyword "machine learning", as observed in two distinct datasets: arXiv publications and patent records.

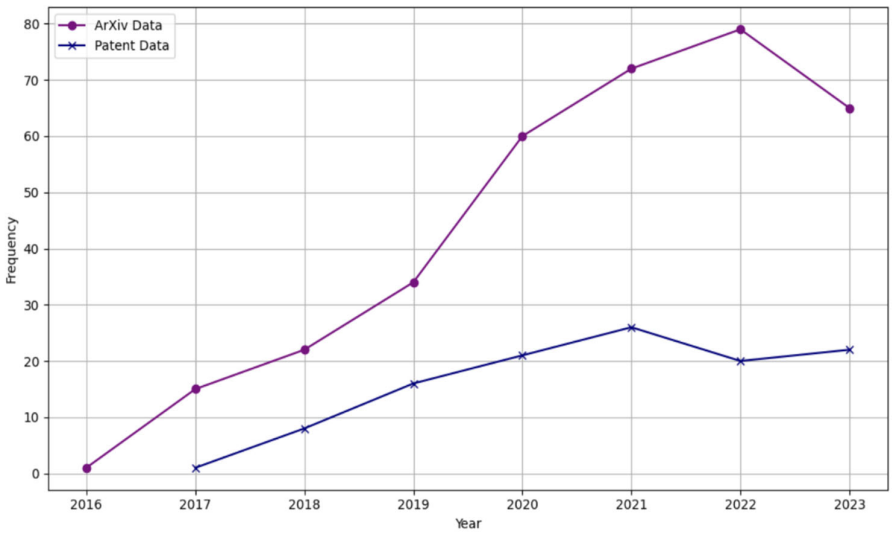


Figure 9. Visualization showcasing a comparative analysis of the yearly trend for the keyword "deep learning", as observed in two distinct datasets: arXiv publications and patent records.

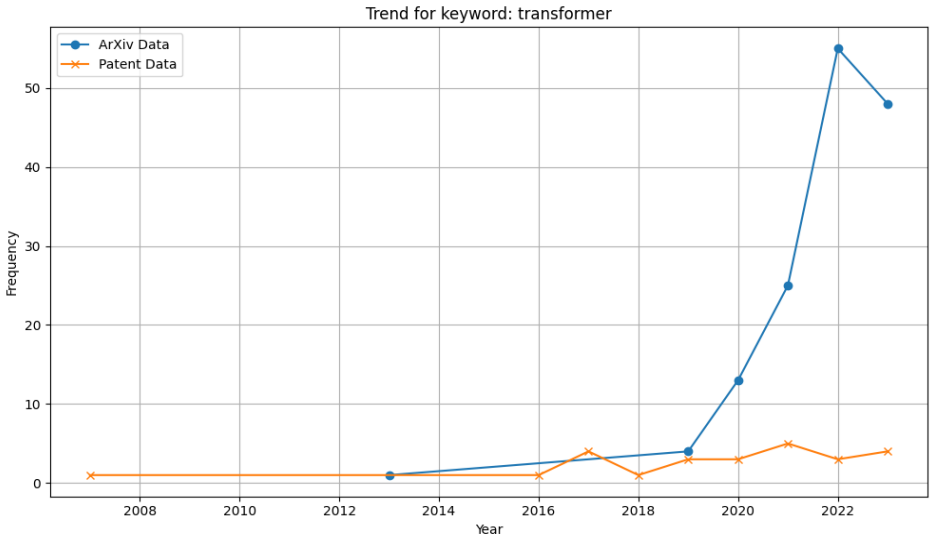


Figure 10. Visualization showcasing a comparative analysis of the yearly trend for the keyword "transformer", as observed in two distinct datasets: arXiv publications and patent records.

It is essential to recognize that pioneering research, including cutting-edge models harnessing transformers for weather prediction, typically undergoes a gradual evolution from academic inception to practical applications that meet the criteria for patenting. For instance, FourCastNet, one of the leading models that utilizes transformers for weather prediction, was unveiled on arXiv in 2022, signaling that it may necessitate additional time before integrating into the patent landscape. Similarly, groundbreaking innovations such as ClimaX, a transformative leap in weather prediction, emerged as recently as 2023, making their immediate appearance in patents less probable [10,11]. These intricacies contribute to the observed delay in the emergence of "transformer" keywords within our patent dataset, underscoring the dynamic nature of technological adoption in the field of weather prediction.

However, we could predict the possible future trend of patents with "transformer" through the remarkable correlation between academic research trends and practical applications, as evident in the keywords "machine learning" and "deep learning". These keywords yielded correlation scores exceeding 90%, signifying a robust alignment between the academic and industrial sectors in the assimilation and advancement of these cutting-edge technologies. In contrast, as mentioned earlier, "transformer" represents a relatively recent development within the broader domain of deep learning, potentially resulting in a slower pace of industry adoption compared with its academic prominence. Consequently, whereas "machine learning" and "deep learning" flourish in both academic research and patent filings, "transformer" is progressively etching its imprint, hinting at an impending transformation in the technological landscape of weather prediction patents. These dynamics underscore the vital importance of sustained monitoring and analysis to accurately capture and comprehend emerging trends.

In this experiment, we analyzed patent data to investigate the publication timelines of patents related to machine learning, deep learning, and neural networks, contrasting them with patents in other domains. We focused on patents filed after 2015 and examined the time difference between the priority date and publication date as a key metric. Our analysis revealed a noteworthy and somewhat unexpected pattern. As Figure 11 shows, patents associated with those keywords exhibited a shorter mean time difference between priority and publication dates compared with patents without these keywords. This implies that, on average, patents in the domain of artificial intelligence (AI) and deep learning technologies tend to be published more rapidly following their initial filing. It could be concluded that AI technologies, marked by their fast-paced innovation and applicability,

may encourage inventors to expedite the patent publication process to stake their claims in a competitive landscape.

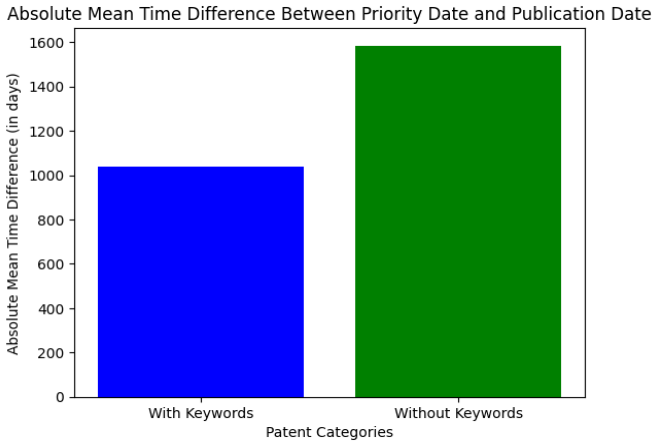


Figure 11. Visualization depicting the absolute mean difference in dates between the priority and grant dates, comparing instances where AI-related keywords are present versus when they are absent.

Moreover, we undertook a comprehensive data preprocessing and feature engineering process to prepare patent data for the task of predicting patent grant durations. Our workflow involved several critical steps. First, we calculated the time span between the priority date and the grant date, a fundamental metric for understanding the patent grant process. To ensure data quality, we converted date columns to datetime objects and handled missing values. Notably, we introduced a categorical representation of grant durations, categorizing spans into "Short Turnaround", "Medium Turnaround", and "Long Turnaround". Additionally, we utilized text vectorization through TF-IDF to convert patent titles into numerical features suitable for machine learning. To facilitate predictive modeling, we converted the categorical grant duration labels into integers using label encoding. Finally, we partitioned the dataset into training and test sets for model evaluation. These data preprocessing and feature engineering steps lay the foundation for subsequent machine learning tasks, enabling the prediction of patent grant durations based on patent titles and categorical duration labels. As Figure 12 depicts, various machine learning algorithms including "GaussianNB", "SVC", "Gradient Boosting", "XG Boost", "LightGBM", and "Extra Tree" were utilized as the classifiers, and the "LightGBM" attained the highest accuracy of 77.02%. For comparison, we also utilized the bidirectional encoder representations from transformers (BERT), but it only achieved about 66.5% accuracy. Even though the highest accuracy was below 80%, this experiment showed the possibility of predicting grant duration using only the title of the patent.

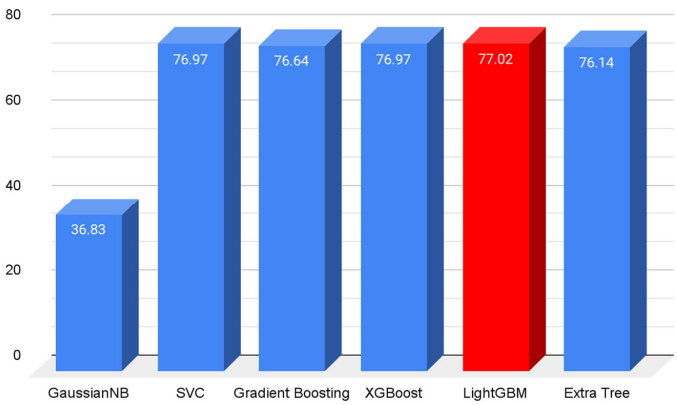


Figure 12. Visualization depicting the accuracy scores of various machine learning models, with red signifying the highest score.

5. Conclusions

This paper explored patent data analysis, uncovering intriguing patterns and trends in the field of weather prediction. Notably, a significant proportion of weather prediction innovations adhered to a common timeline for patenting, with a distinctive peak in grant durations observed between 1500 and 2000 days. This standard timeline reflects the complexities of the patent review process in this domain. The years from 2010 to 2023 witnessed a consistent upward trend in patent grants for weather prediction technologies, with 2020 to 2022 marking periods of heightened innovation. The dataset showcased a global landscape, with the United States, China, and Japan as prominent contributors to weather prediction innovation.

One of the most striking findings was the growing influence of artificial intelligence (AI), exemplified by the emergence of AI-related keywords such as "machine learning" and "neural network". These trends signify a paradigm shift in weather prediction, where data-driven methodologies are increasingly leveraged for improved predictive accuracy [26]. Patents featuring AI-related keywords demonstrated a more condensed publication span in comparison with those lacking such keywords. Furthermore, this research delved into predictive modeling, drawing correlations between data sourced from arXiv and Google Patent. Keywords such as "machine learning" and "deep learning" produced impressive correlation scores exceeding 0.9, indicating that patent trends closely mirror those on arXiv, whereas the "transformer" keyword currently displays a lower correlation score; this can be attributed to its novelty in the tech landscape resulting in an inherent lag in its representation [27].

Although this study provides valuable insights into patent dynamics in weather prediction and the growing influence of artificial intelligence (AI), it is essential to acknowledge its limitations. First and foremost, the predictive modeling aspect of the study, aimed at forecasting patent grant durations based solely on patent titles, exhibited a moderate level of accuracy. The highest accuracy achieved, approximately 77.02%, suggests room for improvement. To address this limitation and further enhance our understanding of patent grant durations, future research could explore the integration of multiple data modalities, such as patent text, images, and structured data [28–30]. Additionally, qualitative analysis through interviews or surveys with patent examiners, applicants, and legal experts could provide valuable insights into the non-textual factors influencing patent grant durations [31,32].

In essence, this study offers valuable insights into the patent dynamics of weather prediction, illuminating the rising prominence of artificial intelligence (AI) and the promising prospects of predictive modeling in patent analysis. By interpreting patent grant durations, understanding innovation hotspots, and tracking recent technologies, this research contributes to a deeper comprehension of the dynamic weather prediction landscape. Moreover, it provides actionable knowledge that can inform decisionmakers in academia, industry, and policy, facilitating informed choices about research directions and resource allocation [33]. As we bridge existing gaps and improve predictive accuracy, the findings presented in this study hold the potential to drive innovation in weather prediction technologies and ultimately enhance our ability to address weather-related challenges in the real world.

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Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

AI	Artificial Intelligence
NWP	Numerical Weather Prediction
PDA	Personal Digital Assistant
LSA	Latent Semantic Analysis
WMD	Weather Modification Device
ETI	Emerging Technological Innovations
IPC	International Patent Classification
CCAT	Climate Change Adaptation Technology
EDA	Exploratory Data Analysis
BERT	Bidirectional Encoder Representations from Transformers

References

1. Lynch, P. The origins of computer weather prediction and climate modeling. *J. Comput. Phys.* **2008**, *227*, 3431–3444. [CrossRef]
2. Berrang-Ford, L.; Ford, J.D.; Paterson, J. Are we adapting to climate change? *Glob. Environ. Change* **2011**, *21*, 25–33. [CrossRef]
3. Trenberth, K.E. Changes in precipitation with climate change. *Clim. Res.* **2011**, *47*, 123–138. [CrossRef]
4. Meehl, G.A.; Zwiers, F.W.; Evans, J.L.; Knutson, T.R.; Mearns, L.O.; Whetton, P. Trends in Extreme Weather and Climate Events: Issues Related to Modeling Extremes in Projections of Future Climate Change. *Bull. Am. Meteorol. Soc.* **2000**, *81*, 427–436. [CrossRef]
5. Schultz, M.G.; Betancourt, C.; Gong, B.; Kleinert, F.; Langguth, M.; Leufen, L.H.; Mozaffari, A.; Stadtler, S. Can deep learning beat numerical weather prediction? *Philos. Trans. R. Soc. A* **2021**, *379*, 20200097. [CrossRef]
6. Chen, N.; Zheng, Q.; Nabney, I.T.; Meng, X. Wind power forecasts using gaussian processes and numerical weather prediction. *IEEE Trans. Power Syst.* **2014**, *29*, 656–665. [CrossRef]
7. Ren, X.; Li, X.; Ren, K.; Song, J.; Xu, Z.; Deng, K.; Wang, X. Deep Learning-Based Weather Prediction: A survey. *Big Data Res.* **2021**, *23*, 100178. [CrossRef]
8. Acumen Research and Consulting. Weather Forecasting Services Market Size Growing at 9.4% CAGR, Set to Reach USD 6.1 Billion By 2032. GlobeNewswire News Room 30 March 2023. Available online: https://www.globenewswire.com/news-release/2023/03/30/2637841/0/en/Weather-Forecasting-Services-Market-Size-Growing-at-9-4-CAGR-Set-to-Reach-USD-6-1-Billion-By-2032.html (accessed on 14 October 2023).
9. Lam, R.; Sanchez-Gonzalez, A.; Willson, M.; Wirnsberger, P.; Fortunato, M.; Pritzel, A.; Ravuri, S.; Ewalds, T.; Alet, F.; Eaton-Rosen, Z.; et al. GraphCast: Learning skillful medium-range global weather forecasting. *arXiv* **2022**, arXiv:2212.12794.
10. Pathak, J.; Subramanian, S.; Harrington, P.; Raja, S.; Chattopadhyay, A.; Mardani, M.; Kurth, T.; Hall, D.; Li, Z.; Azizzadenesheli, K.; et al. Fourcastnet: A global data-driven high-resolution weather model using adaptive fourier neural operators. *arXiv* **2022**, arXiv:2202.11214.
11. Nguyen, T.; Brandstetter, J.; Kapoor, A.; Gupta, J.K.; Grover, A. ClimaX: A foundation model for weather and climate. *arXiv* **2023**, arXiv:2301.10343.
12. Ta, C.; Bm, K.; Gold, E.R.; Sheremeta, L.; Bridge, P. Genetic technologies, health care policy and the patent bargain. *Clin. Genet.* **2002**, *63*, 15–18.
13. *OECD Science, Technology and Industry Working Papers*; OECD: Paris, France, 2010.
14. De Rezende, J.M.; Da Costa Rodrigues, I.M.; Resendo, L.C.; Komati, K.S. Combining natural language processing techniques and algorithms LSA, word2vec and WMD for technological forecasting and similarity analysis in patent documents. *Technol. Anal. Strateg. Manag.* **2022**, 1–22. [CrossRef]
15. Gim, J.; Lee, J.; Jang, Y.; Jung, H. A Trend Analysis Method for IoT Technologies Using Patent Dataset with Goal and Approach Concepts. *Wirel. Pers. Commun.* **2016**, *91*, 1749–1764. [CrossRef]
16. Han, Q.; Heimerl, F.; Codina-Filbà, J.; Lohmann, S.; Wanner, L.; Ertl, T. Visual patent trend analysis for informed decision making in technology management. *World Pat. Inf.* **2017**, *49*, 34–42. [CrossRef]
17. Hötte, K.; Jee, S.J. Knowledge for a warmer world: A patent analysis of climate change adaptation technologies. *Technol. Forecast. Soc. Change* **2022**, *183*, 121879. [CrossRef]
18. Touboul, S.; Glachant, M.; Dechezleprêtre, A.; Fankhauser, S.; Stoever, J. Invention and global diffusion of technologies for climate change adaptation: A patent analysis. *Rev Env. Econ Policy* **2023**, *17*, 316–335. [CrossRef]
19. Google Patents. Available online: https://patents.google.com/ (accessed on 14 October 2023).
20. arXiv.org e-Print Archive. Available online: https://arxiv.org/ (accessed on 14 October 2023).
21. Cohen, W.M.; Levinthal, D.A. Absorptive Capacity: A new perspective on learning and innovation. *Adm. Sci. Q.* **1990**, *35*, 128. [CrossRef]
22. Ahn, J.; Son, H.; Chung, A. Understanding public engagement on twitter using topic modeling: The 2019 Ridgecrest earthquake case. *Int. J. Inf. Manag. Data Insights* **2021**, *1*, 100033. [CrossRef]

23. Ke, G.; Meng, Q.; Finley, T.; Wang, T.; Chen, W.; Ma, W.; Ye, Q.; Liu, T.Y. Lightgbm: A highly efficient gradient boosting decision tree. *Adv. Neural Inf. Process. Syst.* **2017**, *30*.
24. Lee, O.; Joo, H.; Choi, H.; Cheon, M. Proposing an integrated approach to analyzing ESG data via machine learning and deep learning algorithms. *Sustainability* **2022**, *14*, 8745. [CrossRef]
25. Vaswani, A.; Shazeer, N.; Parmar, N.; Uszkoreit, J.; Jones, L.; Gomez, A.N.; Kaiser, Ł.; Polosukhin, I. Attention is all you need. *Adv. Neural Inf. Process. Syst.* **2017**, *30*.
26. Hu, Y.; Chen, L.; Wang, Z.; Li, H. Swinvrnn: A Data-Driven Ensemble Forecasting Model via Learned Distribution Perturbation. *J. Adv. Model. Earth Syst.* **2023**, *15*, e2022MS003211. [CrossRef]
27. Adomavicius, G.; Bockstedt, J.C.; Gupta, A.; Kauffman, R.J. Making sense of technology trends in the information technology landscape: A design science approach. *Mis Q.* **2008**, *32*, 779–809. [CrossRef]
28. Bonino, D.; Ciaramella, A.; Corno, F. Review of the state-of-the-art in patent information and forthcoming evolutions in intelligent patent informatics. *World Pat. Inf.* **2010**, *32*, 30–38. [CrossRef]
29. Jiang, S.; Hu, J.; Magee, C.L.; Luo, J. Deep learning for technical document classification. *IEEE Trans. Eng. Manag.* **2022**, *71*, 1163–1179. [CrossRef]
30. Jiang, S.; Hu, J.; Wood, K.L.; Luo, J. Data-driven design-by-analogy: State-of-the-art and future directions. *J. Mech. Des.* **2022**, *144*, 020801. [CrossRef]
31. Ouyang, K.; Weng, C.S. A new comprehensive patent analysis approach for new product design in mechanical engineering. *Technol. Forecast. Soc. Change* **2011**, *78*, 1183–1199. [CrossRef]
32. Hicks, D.; Breitzman, T.; Olivastro, D.; Hamilton, K. The changing composition of innovative activity in the US—A portrait based on patent analysis. *Res. Policy* **2001**, *30*, 681–703. [CrossRef]
33. Börner, K.; Rouse, W.B.; Trunfio, P.; Stanley, H.E. Forecasting innovations in science, technology, and education. *Proc. Natl. Acad. Sci. USA* **2018**, *115*, 12573–12581. [CrossRef]

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