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Research on Key Technological Breakthroughs of Natural Language Processing Technology in Intelligent Review of Intellectual Property Texts

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Abstract: Intelligent review of intellectual property texts is the core path to break through the efficiency bottleneck of traditional review models and improve review quality. As the core support for text semantic parsing and knowledge mining, the application depth of natural language processing (NLP) technology directly determines the level of intelligent review. This paper systematically analyzes the scene characteristics and technical requirements of intellectual property text review, with a focus on the key breakthrough directions of NLP technology in this field: from the precision of structured extraction of technical features, the depth of cross-modal semantic association, to the systematization of the integration of legal and technical knowledge, and then to the optimization of the interpretability of review decisions. Based on typical practical cases such as "Copyright AI Intelligent Review" in Keqiao and incoPat AI Retrieval, a technical framework of "text parsing - knowledge modeling - intelligent reasoning - decision output" is constructed to reveal the breakthrough paths of technical bottlenecks in each link and look forward to the technological development trends in the era of large models. Provide theoretical support and practical reference for the research and development and optimization of the intelligent intellectual property review system.

Keywords: Explainable AI; Intellectual Property Examination; Knowledge Graph; Large Language Model; Natural Language Processing; Semantic Understanding.

1. Introduction

Under the background of the global innovation-driven development strategy, the number of intellectual property applications has shown an explosive growth trend, and the traditional manual review model is facing severe challenges. According to data from the National Intellectual Property Administration, in 2024 alone, the number of invention patent applications in China reached 1.505 million, and the number of trademark registration applications exceeded 7 million. The contradiction between the massive number of applications and the limited examination resources has become increasingly prominent. The traditional examination mode is highly dependent on manual search, text reading and professional judgment. This process has three core limitations: In terms of efficiency, the average examination period for a single invention patent is as long as 22 months, which is difficult to meet the practical demand for the rapid protection of innovation achievements. At the objective level, the differences in the understanding of technical features and legal provisions among different examiners may lead to inconsistent review conclusions. In terms of coverage, manual search is difficult to comprehensively cover the vast global databases, which may lead to the omission of key comparative literature and affect the accuracy of the review conclusion.

The iterative upgrading of natural language processing technology provides technical possibilities for solving the above-mentioned problems. From the early simple keyword matching to deep learning-driven semantic understanding, and then to the current logical reasoning capabilities of large language models (LLMS), NLP technology has achieved a leap from "text recognition" to "knowledge cognition". The new review system launched by the National Intellectual Property Administration in 2023 has integrated NLP functions such as online translation and intelligent comparison [1]. In 2025, it will further introduce modules like large model search and AI legal assistants, significantly increasing the proportion of retrieved comparative literature. The "Copyright AI Smart Trial" system developed by the Keqiao Court, through the integration of NLP and computer vision technology, enables one-click traceability of pattern Copyrights, with an effective plagiarism detection rate of 61.23%. This has led to a 91.67% reduction in related disputes within three years. All these practices fully demonstrate the application value of NLP technology in intellectual property examination [2].

Internationally, the USPTO (United States Patent and Trademark Office) launched an AI examination pilot as early as 2018, using the BERT model for patent text classification and keyword extraction. The Classification Expert system of EPO (European Patent Office) realizes the automatic classification of patents through NLP technology, with an accuracy rate of over 85% [3]. Domestic research focuses on three major directions: The first is text information extraction. For instance, the patent claim element extraction model proposed by the team from Tsinghua University has an F1 value exceeding 92%. The second is similarity comparison. The multi-modal comparison system built by Alibaba's Copyright Protection Center supports cross-domain similarity judgment between text and graphics. The third is the application of large models. The dedicated search large model trained by the National Intellectual Property Administration has reduced the search time for examiners by 40%[4].

Although the existing research has made phased progress, there are still obvious shortcomings: the structuring degree of technical feature extraction is insufficient, making it difficult to cope with the complex sentence structures of patent texts;

The integration of legal and technical knowledge is not deep, and the model's understanding of legal concepts such as "novelty" and "creativity" is superficial. The lack of interpretability in review decisions and the "black box" problem of large models affect the credibility of review conclusions. This article conducts research on key technological breakthroughs in response to these pain points[5].

This research aims to establish a theoretical system for the application of NLP technology in text review in professional fields, break through the adaptability problem of general NLP technology migrating to the intersection of law and technology, enrich theoretical achievements such as domain adaptive semantic understanding and knowledge graph construction, and provide a new research perspective for intelligent processing of cross-disciplinary texts. The research will identify the key technological breakthrough points of NLP in the review of intellectual property texts, propose practical technical optimization plans, and assist the intelligent review system in achieving the triple goals of "efficiency improvement - quality assurance - cost control"[6].

2. The Scene Characteristics and NLP Technology Requirements of Intelligent Review of Intellectual Property Texts

2.1. Multidimensional Feature Analysis of Intellectual Property Texts

Intellectual property texts cover various types such as patents, trademarks, and Copyrights. Their language expression, structural norms, and knowledge density have distinct professional characteristics. These features constitute the fundamental constraints for the application of NLP technology and also determine the core direction of technology adaptation.

From the perspective of text structure, intellectual property texts possess dual normativity. Take patent documents as an example. They strictly follow the legal structure of "claims - specification - abstract", among which the claims adopt a rigorous expression of "preamble part + feature part", containing a clear logic for defining the scope of protection. The goods/services items in the trademark registration application must strictly correspond to the "Classification of Similar Goods and Services", and the text expression should have strong standardization features[7]. This structural normativity provides an analytical framework for NLP technology, but it also places higher demands on the accuracy of structured information extraction - any minor structural analytical deviation may affect the accuracy of subsequent review and judgment.

From the perspective of semantic expression, intellectual property texts possess dual attributes of both technology and law. The patent claims not only contain the technical description of "technical features + connection relationship", but also imply legal judgment bases such as "novelty" and "inventiveness". Textual evidence in copyright infringement disputes must simultaneously meet the legal requirements of "similarity in expression" and "substantial contact". This dual attribute requires that NLP technology not only accurately parse technical semantics and understand the core logic of technical solutions, but also effectively map technical information with legal concepts, providing semantic support for legal judgments.

From the perspective of the terminology system, the professional and dynamic characteristics of intellectual property texts are prominent. Professional terms from various technical fields form the semantic core of the text, such as "federated learning" and "prompt engineering" in the field of artificial intelligence, and "monoclonal antibody" and "gene editing" in the field of biomedicine, etc. Meanwhile, the rapid iteration of emerging technologies has continuously expanded the terminology system. New terms such as "digital twin Copyright" and "NFT rights confirmation" in the metaverse field frequently appear in review scenarios, which poses a continuous challenge to the terminology adaptation ability of NLP technology and requires the technology to have the ability to update dynamically and learn quickly.

2.2. NLP Technology Requirements for Different Review Scenarios

Different types of intellectual property examination scenarios have different focuses on the demand for NLP technology. This difference stems from the variations in the examination objectives and text features of the scenarios themselves.

The core demands of the patent examination scenario are concentrated in three aspects: Structured extraction of technical features is the foundation. It is necessary to precisely identify technical elements, connection relationships and functional effects from the claims and the specification, and form clear structured semantic units. The retrieval of existing technologies is crucial. It is necessary to achieve cross-database matching of similar technical solutions based on deep semantic understanding. The idea of the incoPat system to precisely compare global patents through the DNA map of technical features is a typical implementation of this demand. The determination of legal elements is the core. It is necessary to semantically associate the extracted technical features with legal standards such as "novelty" and "inventiveness" to assist examiners in making compliant and accurate decisions.

The key demands in the trademark examination scenario revolve around cross-modal integration and semantic determination. Trademark examination often requires the simultaneous processing of text identifiers and graphic elements, which demands that NLP technology achieve cross-modal semantic fusion of text and graphics, accurately capturing the correlation between the two. The automatic determination of similar goods/services requires that the technology be able to match the standard expressions in the "Classification Table of Similar Goods and Services" based on text semantics. The semantic analysis of trademark distinctiveness requires mining from the text whether the mark has the core function of "distinguishing the source of goods" to avoid conflicts with prior rights. When handling trademark conflict reviews, the "Copyright AI Intelligent Review" system in Keqiao needs to meet these technical requirements simultaneously[8].

The core demands of the copyright review scenario focus on originality determination and infringement detection. Originality determination requires the identification of "substantial similarity" through text semantic comparison to distinguish the boundary between ideas and expressions. Infringement detection needs to combine metadata such as timestamps to trace the creation sequence and determine whether there is a possibility of "substantial contact". The relevant system of the Keqiao Court has successfully resolved multiple copyright ownership disputes by analyzing the publication time and content features in web page texts through NLP technology. This practice also confirms the core direction of the demand for NLP technology in the copyright review scenario[9]. As shown in Table 1, the main scenarios for the review of intellectual property texts and the corresponding NLP technical requirements are listed.

Table 1. The main scenarios of intellectual property text review and the corresponding NLP technical requirements

Review scenarios	Core NLP technology requirements	Application value (Commonality)
Patent examination	1.Structured extraction of technical features 2.Semantic retrieval of existing technologies 3.Semantic Matching of legal elements	1. Enhance review efficiency 2. Ensure the quality of review 3. Reduce labor costs
Trademark examination	1.Cross-modal semantic fusion 2.Classification determination of goods/ services 3. Significance semantic analysis	1.Enhance review efficiency 2. Ensure the quality of review 3. Reduce labor costs
Copyright examination	1.Determination of substantial similarity 2. Tracing the origin of the creative sequence 3. Extraction of ownership information	1.Enhance review efficiency 2. Ensure the quality of review 3. Reduce labor costs

3. Key Technological Breakthroughs in Natural Language Processing in the Review of Intellectual Property Texts

3.1. Structured Extraction and Precise Analysis of Technical Features

Technical feature extraction is a fundamental step in the review of intellectual property texts, and its accuracy directly affects the accuracy of subsequent similarity comparisons and legal judgments. Traditional keyword extraction methods are difficult to handle the complex semantic structure of technical texts, and there is an urgent need to transform from "planar extraction" to "structured modeling". This transformation process requires breaking through three core technical points.

Multi-task learning provides an effective path for the extraction of technical elements. For the hierarchical relationship of technical features in patent texts, a multi-task model of "entity recognition - relation extraction - attribute annotation" can be constructed. BERT-WWM is adopted as the basic encoder, and information complementarity among tasks is achieved by sharing the underlying semantic representation. In the entity recognition task, define 12 types of entity labels such as "technical components", "action methods", and "functional effects"; In the relation extraction task, identify eight types of core relationships such as "component-connection" and "method - implementation"; In the attribute annotation task, annotate attribute information such as "material", "parameter", and "applicable scenario". Experimental data show that on patent texts with IPC classification number G06F, the F1 value of entity recognition of this model reaches 94.2%, and the F1 value of relationship extraction reaches 89.7%, significantly outperforming the single-task model. This multi-task collaborative approach effectively resolves the problems of incomplete extraction of technical elements and ambiguous relationship recognition.

The semantic structured modeling of the claims requires the dual support of grammar and semantics. The writing of the claims follows strict logical rules, and its semantic structure can be abstractly defined as "technical subject + feature set + protection boundary". In view of this feature, a semantic parsing framework based on grammar enhancement can be proposed: Firstly, through dependency syntactic analysis, the core grammatical units such as the "de" character structure and verb-object phrases are identified to clarify the grammatical logic of the text; Utilize pre-trained language models (such as LawBERT) to capture the cross-semantics of law and technology and understand the professional connotations of the text; Finally, output the structured representation of the "feature tree" to transform the abstract text into clear semantic units. Take "A Medical Data Processing Method Based on Federated Learning" as an example. The model can automatically parse out structured information such as "Subject: Medical data processing method", "Core Feature: Federated Learning", and "Auxiliary feature: Data desensitization, model aggregation", providing clear semantic units for subsequent comparisons and avoiding review errors caused by semantic understanding deviations[10].

The terminology adaptation mechanism in low-resource domains is the key to dealing with the review of emerging technologies. To address the issue of insufficient corpora in emerging technology fields, an adaptation system of "general term database - domain term migration - dynamic update" can be constructed: Based on CNKI and the patent abstract database, a general database containing 500,000 terms can be built to provide fundamental support for term recognition. The Domain-Adaptive Pre-training method is adopted to transfer the general model to specific fields such as new energy and AI, improving the adaptability of the model in professional fields. Design a dynamic update module for terms, monitor and review high-frequency new words, and combine manual verification to achieve real-time expansion of the term database. Tests on the patent corpus of new energy vehicles show that this mechanism has increased the accuracy rate of term recognition from 82.1% to 91.5%, effectively solving the problem of lagging term recognition in emerging technology fields[11]. As shown in Figure 1, the architecture of the multi-task learning model.

3.2. Semantic Similarity Calculation Across Modalities and Domains

Intellectual property examination often requires handling cross-modal data such as "text-graphics" and cross-domain semantics such as "technology-law". Traditional single-modal and single-domain similarity calculation methods have obvious limitations, and it is urgent to build a semantic comparison framework that integrates multi-source information. The construction of this framework needs to break through from three dimensions.

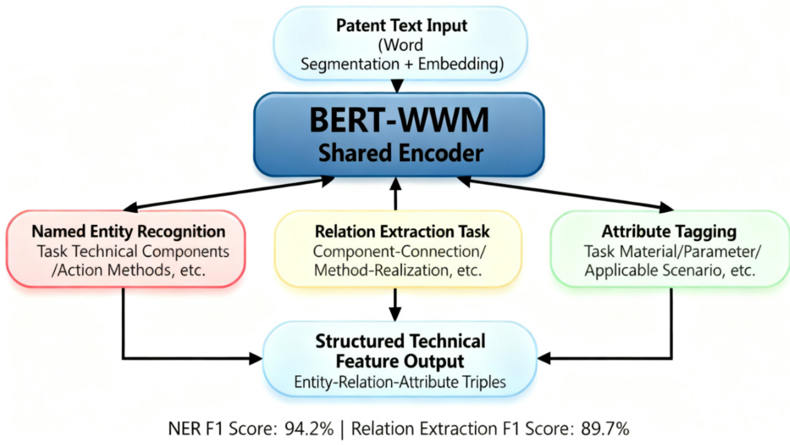

Figure 1. Architecture of the multi-task learning model

The cross-modal semantic fusion of text and graphics is the core technical requirement of trademark and copyright examination. In trademark and copyright examination, the similarity judgment between textual descriptions and graphic elements is often the key. To meet this demand, a cross-modal fusion model based on contrastive learning can be proposed: the text branch uses RoBERTa to extract semantic vectors to capture the semantic connotation of the text; The graphic branch adopts Vision Transformer (ViT) to extract visual features and recognize the visual features of the graphics. Feature space alignment is achieved through the cross-modal contrast loss function to ensure that text and graphics have comparability in the same feature space. At the same time, introduce the "semantic consistency constraint" to ensure that the "red circle" in the text description has similar feature representations to the corresponding visual elements in the graphics, avoiding the problem of "semantic disconnection between text and graphics". After the "Copyright AI Intelligent Review" system in Keqiao adopted this technology, it achieved precise comparison between the text descriptions and patterns of artworks, with a similarity judgment accuracy rate of 92.3%, significantly enhancing the efficiency and accuracy of the review[12].

Knowledge enhancement provides a bridge for cross-domain semantic matching. There is a natural semantic gap between technical texts and legal texts. To achieve an effective match between the two, it is necessary to build a fusion system of "technical knowledge graph - legal knowledge graph - cross-domain alignment" : The technical knowledge graph contains 2 million technical entities and relationships, covering the core concepts of the main technical fields. The legal knowledge graph covers 50,000 legal concepts and provisions in laws and regulations such as the Patent Law and the Trademark Law, clarifying the standards for legal judgment. Cross-domain alignment is achieved through "entity linking - concept mapping - rule reasoning", for instance, by conceptually mapping "gene editing technology" with Article 25 of the Patent Law, "Diagnosis and treatment methods for diseases", to establish semantic associations between technology and law. In similarity calculation, the introduction of a knowledge attention mechanism enables the model to prioritize technical features related to legal provisions. This optimization, in the scenario of patent novelty judgment, increases the matching accuracy by 15.6%, effectively addressing the disconnection between technical and legal semantics.

Context-aware similarity ranking algorithms are the key to improving the accuracy of retrieval. Traditional similarity calculation ignores the context weight differences of technical features, resulting in the equal treatment of core features and secondary features, which affects the accuracy of retrieval results. To address this issue, a ranking model based on bidirectional attention can be proposed: In the retrieval stage, drawing on the idea of the "technical feature DNA map" of the incoPat system, the structured features of the target patent are transformed into semantic vectors to ensure the integrity of the feature representation; In the ranking stage, the context similarity between the target features and the candidate patent features is calculated through the bidirectional attention mechanism, and the weights of different features in specific contexts are clarified. Combine the "core feature weight doubling" strategy to output the final ranking result, highlighting the influence of core technical features. Experimental data show that in the invalid search scenario, this algorithm has increased the proportion of relevant patents entering the top 10 to 87.2%, far exceeding the 62.5% of the traditional TF-IDF method, significantly improving the accuracy and efficiency of the search. As shown in Figure 2, it is a cross-domain semantic matching framework.

3.3. Modeling of the Integration of Legal and Technical Knowledge

The essence of intellectual property examination is a process of judging technical solutions based on legal rules. To achieve the intelligence of this process, it is necessary to break through the semantic disconnection between "technical features" and "legal provisions", and achieve a deep integration at the knowledge level. This integration process needs to be advanced from three levels.

The structured representation and semantic analysis of legal provisions are the foundation of knowledge fusion. Legal provisions are often abstractly expressed, making it difficult to directly apply them to technical judgments. They need to be transformed into structured and computable semantic units. Legal provisions can be analyzed into a ternary structure of "constituent elements - applicable circumstances - legal consequences", and the ontology modeling method is adopted to construct the legal knowledge ontology and clarify the logical structure of the provisions. Taking the "Inventiveness" clause of Article 22 of the Patent Law as an example, structured information such as "Constituent elements: having outstanding substantive features and significant progress", "applicable circumstances:

compared with existing technology", and "legal consequences: Grant of patent right/rejection of application" can be analyzed, transforming the abstract clause into clear judgment criteria. Meanwhile, the semantic encoding of the clause text is carried out through LegalBERT to generate vector representations containing legal elements, providing computable legal basis for subsequent reasoning and avoiding judgment errors caused by deviations in clause understanding.

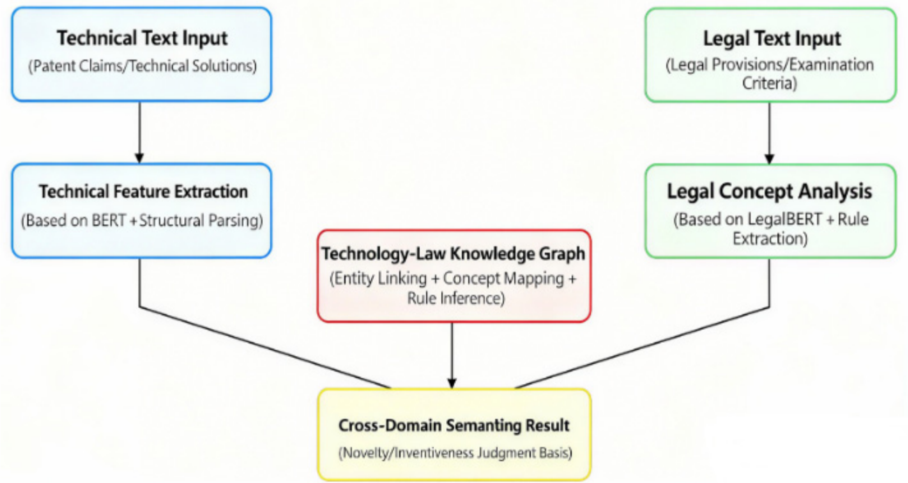

Figure 2. Framework diagram of cross-domain semantic matching

The construction and application of the Technology-Legal Knowledge Graph (IP-KG) is the core carrier of knowledge fusion. Build a knowledge graph that integrates technical entities, legal concepts, and review cases, including three types of nodes: technical entities, legal concepts, and review cases, as well as five types of relationships: "technology - applicable provisions", "Provisions - cases", and "cases - technical fields", to form a complete knowledge association network. The automated construction process of "entity linking - relationship extraction - case entry" is adopted. Among them, the relationship extraction uses the Few-Shot learning method, and a small number of manually annotated cases are used to achieve model training, reducing the annotation cost while ensuring the extraction accuracy. During the examination process, IP-KG can provide chain reasoning support of "technical features → relevant provisions → reference cases". For instance, when the technical feature of "gene-edited embryos" is detected, the system can automatically associate it with Article 25 of the Patent Law and push relevant rejection cases, providing comprehensive knowledge support for examiners and achieving a deep integration of technology and law.

Legal logical reasoning based on large models is an advanced application of knowledge fusion. For the complex legal judgment problems in the review, a reasoning framework of "retrieval enhancement - logical chain generation - conclusion verification" needs to be constructed: Firstly, relevant legal provisions and reference cases are obtained from IP-KG and the case library through the retrieval module to provide factual basis for reasoning; Then, the large model after Instruction Tuning (such as ChatGLM - Legal version) is adopted to generate the logical chain of "technical analysis → clause application → conclusion derivation", clarifying the basis of each step of the reasoning process; Finally, the conclusion is verified through the rule base of legal experts to ensure that the reasoning complies with legal norms and avoid logical loopholes or errors in the application of the law. The AI legal assistant module of the National Intellectual Property Administration adopts similar technology to achieve intelligent question-and-answer for legal article search and case analysis, effectively enhancing the legal application ability of examiners and promoting the transformation of the examination process from "experience-dependent" to "knowledge-driven". As shown in Figure 3, it is the modeling framework for the integration of legal and technical knowledge.

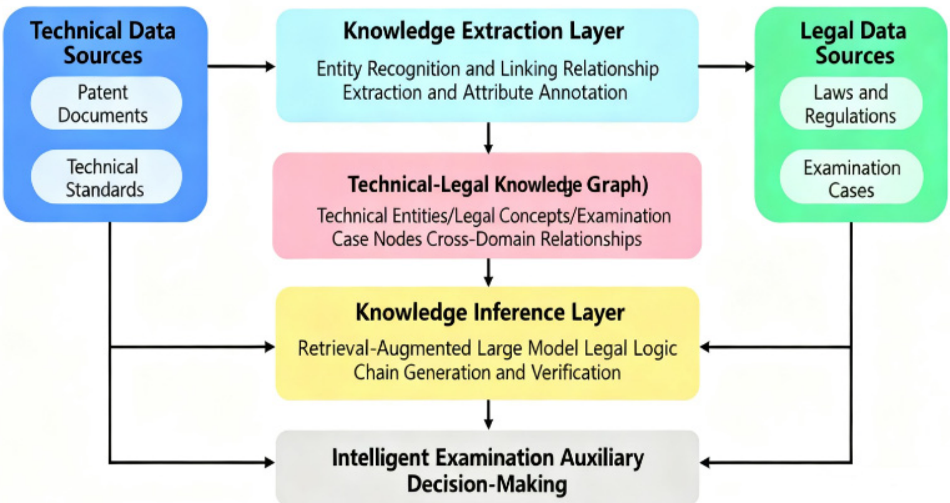

Figure 3. Framework diagram for modeling the integration of legal and technical knowledge

3.4. Optimize the Interpretability and Enhance the Credibility of Review Decisions Modeling of the Integration of Legal and Technical Knowledge

The "black box" nature of large models leads to a lack of transparency in review decisions, making it difficult to meet the traceability requirements of intellectual property reviews and also affecting the trust of examiners in the model's conclusions. To solve this problem, breakthroughs need to be made in both model architecture design and output presentation to achieve "explainable decisions and verifiable results".

Local explanations based on attention visualization can help reviewers understand the basis for model decision-making. In the technical feature extraction and similarity comparison module, the attention weight visualization function is integrated. The Grad-CAM method is adopted to generate the text heat map, highlighting the core semantic units relied on by the model decision. For instance, in the determination of patent similarity, the heat map can visually present the "core technical features" and "distinguishing technical features" that the model focuses on. Through the heat map, examiners can quickly grasp the judgment logic of the model and understand why two patents are determined to be similar or dissimilar. When handling the judgment of graphic similarity, the "Copyright AI Intelligent Review" system in Keqiao also displays the key feature matching areas and similarity scores of similar images, making the decision-making basis clear at a glance and significantly enhancing the credibility of the decision-making results.

4. Typical Application Cases and Technical Effectiveness Verification

4.1. Patent intelligent Examination Assistance System

Table 2. Comparison Table of Efficiency Improvement of Patent Intelligent Examination Assistance System

Evaluation Indicator	AI Examination System	Traditional Manual Examination
Feature Extraction Accuracy	93.1%	80%
Search Time Consumption	0.8h	4.5h
Conclusion Adoption Rate	82.6%	~67%

Based on the above key technologies, a patent intelligent examination assistance system is developed, integrating four functional modules: "text parsing - knowledge modeling - intelligent retrieval - auxiliary judgment". In a pilot application at a certain examination center of the National Intellectual Property Administration, 1,000 invention patent applications were selected for testing, and the results showed that: The accuracy rate of the system's automatic completion of technical feature extraction reached 93.1%. The average time consumption for similar literature retrieval was reduced from 4.5 hours manually to 0.8 hours. The adoption rate of the system's auxiliary conclusions by examiners was 82.6%, and the average examination cycle for a single patent was shortened by 3.2 months. As shown in Table 2, the performance improvement comparison of this system is presented.

4.2. The "Copyright AI Intelligent Review" System of Keqiao

This system deeply integrates NLP and computer vision technologies to build an intelligent review system covering the entire life cycle of copyright. The automatic extraction of work ownership information is achieved through text semantic parsing, combined with the analysis of web page text timestamps to trace the creation sequence, and based on cross-modal similarity calculation to realize infringement detection.

As of September 2024, the system has accepted 6,937 duplicate check cases from 187 courts in 14 provinces, and identified 4,235 cases of prior use, effectively supporting the improvement of judicial trial efficiency. In the application of the Light Textile City Market, 33,000 business operators have self-checked for plagiarism through the mini-program, reducing copyright disputes over patterns by 91.67% in three years, fully demonstrating the practical value of NLP technology.

4.3. incoPat AI Retrieval System

This system adopts a fusion architecture of "technical feature DNA map + large model" to achieve precise retrieval in scenarios such as novelty search, invalidation, and infringement risk. By using NLP technology to transform patent texts into structured technical feature maps and combining the semantic understanding capabilities of LLMS, the matching accuracy is enhanced.

In the invalid search scenario test, the optimized algorithm increased the proportion of X files entering the top 10 of the search results by more than 40%, and at the same time supported the automatic generation of search reports and the visualization of feature comparison, significantly improving the efficiency of enterprise patent layout and risk prevention and control.

5. Challenges and Future Prospects

5.1. The Main Challenges Currently Faced

Although natural language processing technology has demonstrated significant value in the field of intellectual property text review, the implementation and large-scale application of the technology still need to overcome multiple practical bottlenecks. At the data level, high-quality labeled data is the core support for improving the performance of NLP models. However, intellectual property data often contains the applicant's sensitive technical solutions and personal privacy information. During the process of data sharing and labeling, compliance risks are easily faced - for example, if the core technical parameters in the patent application documents are leaked, it may directly affect the applicant's competitive advantage in the market. How to strike a balance between fully leveraging the value of data and strictly protecting privacy and security has become a key issue restricting technological development.

The domain adaptation ability of the model also has limitations. The existing technical solutions have achieved relatively good performance in traditional technical fields such as mechanics and electronics. However, when transferred across fields to emerging fields like quantum computing and brain-computer interfaces, the model performance often experiences a significant decline. Professional corpora in such emerging fields are already scarce, and the speed of technological iteration is fast with frequent updates in the terminology system, which makes it difficult for models to quickly adapt to the review requirements of new fields and unable to form stable and reliable technical support.

The dynamic evolution of legal concepts also poses challenges to technological adaptation. Laws and regulations are constantly revised along with social development and judicial practice, and new legal issues keep emerging. For instance, topics such as "copyright ownership of works generated by artificial intelligence" and "intellectual property definition of NFT digital assets" have yet to reach a unified consensus on their legal semantics. If the model fails to capture these changes in real time, the understanding of legal concepts is likely to remain at a static level, which in turn affects the legality and accuracy of the review conclusion.

In addition, the limitations of computing resources and implementation costs cannot be ignored. The training and inference of large models require high-performance computing equipment and continuous computing power support, which poses a too high threshold for small and medium-sized review institutions and innovative enterprises with limited financial and technical strength. Although many small and medium-sized entities have the need for intelligent review, they are unable to afford the hardware investment and maintenance costs, and thus find it difficult to enjoy the dividends of technological development, which limits the application scope of the technology.

5.2. Future Development Trends

In response to current challenges and in line with the direction of technological evolution, the development of natural language processing in the field of intellectual property examination will present a multi-dimensional breakthrough trend in the future. To lower the application threshold, the integration of lightweight models and edge computing has become an important direction. Through technologies such as knowledge distillation and quantization compression, large models with tens of billions of parameters can be streamlined to a scale of tens of millions. While ensuring core performance, the demand for computing resources is significantly reduced, making them compatible with edge computing devices. This lightweight solution can effectively reduce the investment costs of small and medium-sized institutions and promote the penetration of technology into a wider range of scenarios.

In the field of data privacy protection, the application of federated learning frameworks will provide a new path for multi-agent collaboration. Without sharing the original data, intellectual property bureaus and enterprises in multiple regions can train sub-models based on local data, and then update and optimize the global model through the aggregation of encrypted parameters. This not only avoids the risk of sensitive data leakage but also integrates the value of multi-source data, enabling the model to further enhance its generalization ability on the basis of fully learning the data features of different scenarios. Achieve the collaborative effect of "data available but not visible".

The deep integration of multimodal large models will break the limitations of a single type of information. The future intelligent examination system will no longer be limited to processing text data, but will be capable of simultaneously parsing multi-source information such as patent texts, drawings, experimental data, and graphic trademarks. For instance, based on multimodal models like GPT-4V, it can achieve a linked analysis of "text description - technical drawings - effect data", providing a more comprehensive understanding of the core characteristics of intellectual property objects. Provide more precise technical support for cross-modal review scenarios (such as judging the similarity of trademark graphics and text, and cross-form comparison of copyright works).

The combination of intelligent review and digital twin technology will also promote the construction of an intelligent closed loop in the review process. By building a digital twin system for intellectual property examination, NLP technology can be deeply integrated with the digital module of the examination process - simulating the examination process of different technical solutions in a virtual scene and optimizing model parameters based on the simulation results. Meanwhile, the data from the actual review is fed back to the twin system, and the process design is continuously iterated. Eventually, a positive cycle of "technology iteration - process optimization - efficiency improvement" is achieved, making intelligent review not only a tool upgrade but also a systematic innovation of the entire review system.

6. Conclusion

Natural language processing technology is profoundly reshaping the underlying logic of intellectual property text review, driving the industry to gradually transform from the traditional human-led "empirical judgment" model to the AI-assisted "data-driven decision-making" model. The research in this paper indicates that to achieve this transformation, the structured extraction of technical features, cross-modal semantic fusion, and the modeling of legal-technical knowledge and the optimization of the interpretability of review decisions are the four core directions that must be broken through.

Through multi-task learning to enhance the accuracy of technical feature extraction, relying on knowledge graphs to build a bridge of connection between law and technology, and leveraging large models to strengthen logical reasoning capabilities, these technological innovations have demonstrated their value in addressing the pain points of traditional review in practice - the reduction of dispute rates by the "Copyright AI Intelligent Review" system in Keqiao, and the improvement of search efficiency by incoPat AI retrieval All of these confirm the practical significance of technological breakthroughs. However, it is also necessary to face up to the fact that issues such as data privacy protection, domain generalization capabilities, and dynamic legal adaptation remain major challenges that need to be continuously overcome in the future.

Looking ahead, only by developing lightweight models to lower application thresholds, leveraging federated learning to balance data utilization and privacy protection, and relying on multimodal fusion to expand technological boundaries, can the adaptability and practicality of NLP technology in the field of intellectual property examination be further enhanced. With the continuous evolution of these technologies, natural language processing will no longer be a simple "auxiliary tool", but will become the "core pillar" supporting the efficient operation of the intellectual property examination system, providing a solid technical guarantee for building a more efficient, accurate and fair intellectual property protection ecosystem.

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