Multi-Task Learning-Based AI System for Legal Judgment Logic Prediction in Economic Law Litigation

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This study proposes a judgment logic prediction system tailored for economic law litigation by leveraging a multi-task deep learning architecture. The system integrates natural language processing and structured data analysis to address the complexity and volume of legal cases. A dataset of 1,000 corporate bankruptcy cases was constructed, with 800 for training and 200 for testing. Experimental results demonstrate that the proposed MTLPN model achieves an accuracy of 89.3%, outperforming traditional models such as SVM (79.2%) and Random Forest (81.7%). The mean average precision reached 81.4%, and the system reduced average reasoning time to 1.2 seconds per case. Additionally, judgment consistency among judges increased from 78.2% to 91.3% in test scenarios. This study highlights significant improvements in efficiency, accuracy, and transparency in economic law case handling, validating the system's value in supporting judicial decision-making and promoting fairer outcomes.

Povzetek: Študija predstavi večopravilni globoki model (MTLPN) za napovedovanje sodnih izidov v gospodarskem pravu, ki združi obdelavo pravnih besedil in strukturiranih podatkov ter izboljša natančnost, hitrost in usklajenost odločanja.

1 Introduction

Economic law litigation is an important legal procedure for handling disputes in economic fields such as enterprises, markets, taxation, and intellectual property rights. In modern society, with the increasing complexity of economic activities and the acceleration of the globalization process, the number of economic law litigation cases has shown an upward trend, and the types of cases have become more diverse [1, 2]. The legal provisions, precedents, and legal theories involved in this field are complex and complicated. The judgment of a case often requires comprehensive consideration of a large number of evidence, legal application, legal principles, and precedent guidance. Economic law litigation requires judges to have not only profound legal literacy, but also an in-depth understanding of the economic activities of the relevant industry [3]. However, in the face of the increasing number of cases, the work pressure of the court has risen sharply, and the case trial cycle has gradually become longer. The extension of the case trial cycle not only affects the protection of the rights and interests of the parties, but may also lead to the problem of low judicial efficiency [4]. In addition, the process of judging economic law cases is full of uncertainty. Judicial personnel need to make professional judgments in complex and changing case situations. Different judges may make different judgments based on the same case. This difference leads to a huge gap in judicial discretion, which in turn affects judicial fairness and the public's trust in the judicial system [5]. In this context, how to use technological means to improve judicial efficiency, reduceuncertainty in judgments, and achieve fair and just judgments have become a pressing issue that needs to be addressed [6].

With the increasing complexity of economic activities and globalization, the number of economic law litigation cases has grown rapidly. These cases are diverse in type and span a wide range of fields, placing significant pressure on the judicial system. The traditional manual trial process is often inefficient and results in lengthy judgment cycles. Additionally, due to the complexity of the cases and variability in judges' personal experience, outcomes may lack consistency, thereby affecting judicial fairness and transparency [7]. In this context, the integration of artificial intelligence (AI) technologies and the development of a judgment logic prediction system hold substantial practical significance and research value. AI systems can efficiently analyze large volumes of historical data, identify patterns in legal decision-making, support judicial decision-making, improve overall efficiency, and strengthen public confidence in judicial fairness [8].

This study focuses on the application of artificial intelligence in economic law litigation, with an emphasis on the design and implementation of a judgment logic prediction system based on deep learning. The research includes the construction of a dataset of economic law cases, feature extraction and data preprocessing, the design of a deep learning model tailored to economic law, and the development of functional modules to perform logic prediction. System performance is verified through experiments, and its impact on judicial efficiency and fairness is analyzed [9].

Artificial intelligence has achieved significant advancements across various fields, particularly in natural language processing, pattern recognition, and data analysis. In recent years, its application in the legal domain has received growing attention. As an innovative technological tool, a judgment logic prediction system based on AI can assist judges by analyzing historical cases, legal reasoning, and underlying legal rules within court documents, thus enhancing the accuracy of judgments. The application of AI in economic law litigation offers considerable practical value and academic importance.

This study investigates whether a deep learning-based judgment logic prediction system can enhance the efficiency, accuracy, and consistency of decisions in economic law litigation. The core research problem lies in the unpredictable nature of current judgments and the prolonged trial cycles due to the complexity of legal provisions and case structures. The expected outcome is the development of a multi-task AI system capable of accurately predicting verdicts, identifying relevant legal provisions, and explaining decision logic. By doing so, the study aims to provide a scalable and interpretable solution that addresses the overload faced by courts and reduces inconsistencies in legal reasoning within the field of economic law.

This study aims to address the growing challenges in economic law litigation, particularly the inefficiency, subjectivity, and lack of consistency in judicial decision-making. The core research objective is to design and implement an artificial intelligence system that can predict legal judgment logic accurately and transparently in economic law cases. Specifically, the study investigates how deep learning models — especially multi-task architectures—can process both legal texts and structured data to generate interpretable judgment predictions. The central research questions include: (1) How can AI effectively extract and integrate key features from legal documents and case metadata in economic law litigation? (2) Can a multi-task learning model improve judgment accuracy and interpretability compared to traditional models? (3) What measurable impact does the system have on trial efficiency and judicial consistency? These questions guide the design, implementation, and evaluation of the proposed AI system throughout the study.

2 Literature review

2.1 Characteristics and challenges of economic law litigation

Economic law litigation involves areas such as commercial transactions, financial activities, and market competition. These cases are characterized by high complexity, diverse legal relationships, and extensive volumes of evidence. In recent years, with the advancement of global economic integration and the digital economy, economic law cases have exhibited new characteristics and challenges. Modern economic activities often involve complex transactional structures between enterprises, multiple stakeholder interests, and intricate contractual arrangements [10]. This requires judges to possess a comprehensive understanding of business models and to apply relevant legal provisions accurately during the litigation process.

With the growth of information technology, electronic evidence has become increasingly significant in economic law litigation. New forms of digital evidence, such as emails, electronic contracts, and digital signatures, present challenges in terms of collection, preservation, and authentication. Additionally, the rise of cross-border trade and investment has increased the complexity of legal issues in economic litigation. Differences in legal systems across countries and regions further complicate adjudication. Due to case complexity and the volume of evidence, economic law litigation often entails prolonged trials, which leads to higher litigation costs and reduced judicial efficiency. In summary, the complexity and diversity of economic law litigation impose greater demands on the judicial system [11], highlighting the urgent need to enhance trial efficiency and ensure the accuracy and fairness of judgments.

2.2 Current status of AI application in law

The application of artificial intelligence (AI) technology in the legal field, particularly in judgment prediction, has advanced considerably in recent years. By utilizing deep learning and natural language processing techniques, AI systems are capable of analyzing large volumes of legal texts and assisting legal professionals in decision-making. In the area of legal judgment prediction, researchers have employed deep learning models to analyze legal documents and predict case outcomes [12]. For instance, one study proposed an attention-based model to predict the outcomes of second-degree murder and corruption cases using text data from the Brazilian legal system. Another study conceptualized the judgment prediction task as a legal reading comprehension problem and introduced the AutoJudge model [13]. This model predicts final judgment outcomes by analyzing the semantic relationships among case facts, the plaintiff's claims, and applicable legal provisions.

In the domain of legal knowledge graph construction and application, researchers have improved case representation and prediction accuracy by integrating structured knowledge. One study introduced a legal judgment prediction method based on knowledge graphs, enhancing semantic representation by linking case features with structured legal knowledge and enabling judgment link prediction [14,15]. Additionally, in the areas of legal element extraction and multi-task learning, some researchers have proposed prediction models based on legal documents. These models decompose the overall task into three subtasks: legal article prediction, crime classification, and sentencing prediction, with separate models constructed for each [16]. Despite these advancements, several challenges remain. The specialized and complex nature of legal texts imposes high demands on language processing technologies. Moreover, as legal decisions often involve ethical and social value judgments, the current capabilities of AI systems in addressing such dimensions remain limited [17].

2.3 Analysis of existing decision prediction systems

At present, a variety of AI-based judgment prediction systems have been proposed and applied. These systems mainly use technologies such as deep learning, natural language processing, and knowledge graphs to analyze and process legal texts and assist legal practitioners in making judgment predictions. In terms of model selection, some studies have used traditional machine learning models such as support vector machines and neural networks for judgment prediction [18]. However, with the rise of deep learning, convolutional neural networks (CNNs), recurrent neural networks (RNNs), and models based on attention mechanisms have shown better performance in judgment prediction. For example, some studies have used hierarchical attention networks (HANs) to model legal texts and achieved a high prediction accuracy. In terms of feature representation, traditional methods mainly rely on artificial feature engineering to extract features such as keywords and word frequencies for modeling [19]. However, this method is difficult to capture the deep semantic information in legal texts. To this end, researchers have introduced distributed representation methods such as word vectors and sentence vectors, and used pre-trained language models (such as BERT) to represent legal texts, thereby improving the model's expressive power. In terms of multi-task learning, some studies have decomposed the judgment prediction task into multiple subtasks [20], such as legal article prediction, crime prediction, and sentence prediction, and improved the generalization ability and prediction accuracy of the model through multi-task learning. Although the existing judgment prediction system has improved the accuracy and efficiency of prediction to a certain extent, there are still some shortcomings. First, the complexity and professionalism of legal texts make it difficult for the model to fully understand its meaning, which may lead to deviations in the prediction results. Second, the model has poor interpretability, making it difficult for users to understand its prediction process and basis [21, 22]. In addition, legal judgments involve ethical and social value judgments, and the ability of AI systems in this regard still needs to be improved.

Recent studies have introduced various models for legal judgment prediction, such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), hierarchical attention networks (HANs), and transformer-based models like BERT. While these approaches have shown progress in criminal or civil domains, most focus on single-task outputs and lack integration of structured metadata. This study advances the field by proposing a multi-task learning model (MTLPN) specifically designed for economic law litigation, incorporating both legal text and structured features like case type, party roles, and cited laws. Compared to models like AutoJudge and LJP-BERT, which mainly rely on legal texts, the proposed system demonstrates superior performance by combining semantic understanding with metadata-driven context. Additionally, unlike existing methods that often sacrifice interpretability, the use of attention mechanisms and feature weighting in this study provides transparent explanations for legal predictions, which is crucial for judicial trust and accountability.

3 Design of artificial intelligence judgment logic prediction system

3.1 System objectives and functions

The core objective of the AI judgment logic prediction system is to enhance the efficiency, accuracy, and transparency of economic law litigation. In traditional trials of economic law cases, the complexity of legal provisions and the substantial volume of case information often result in lengthy proceedings and potentially subjective judgments. By integrating artificial intelligence technology, the system enables automation and intelligent processing of cases, offering scientific support to judges and significantly improving the efficiency of judicial workflows.

The system is primarily designed to improve the accuracy of judgment predictions. By leveraging deep learning models to analyze legal documents, historical rulings, and relevant legal provisions, the system can identify key features of a case and generate high-confidence predictions based on historical patterns. To ensure practical applicability, the system also emphasizes the interpretability of judgment logic. It clearly presents the reasoning behind its predictions, including cited laws and weighted features, thereby fostering understanding and trust in the system's outputs.

Another goal of the system is to optimize the case-handling process. Automated data preprocessing and feature extraction significantly reduce analysis time and ease the workload of courts and judges. Furthermore, the system supports the prediction of various case types through a modular design, providing strong scalability and adaptability for diverse legal scenarios.

The system's functional modules include data input, feature extraction, model training and optimization, and judgment prediction output. The input module accommodates multiple data formats. The extraction module uses natural language processing techniques to identify case categories, party information, and legal citations. The training module applies deep learning models to execute prediction tasks, while the output module presents results along with explanatory details. The overall architecture is designed to deliver accurate, efficient, and transparent technical support for the judicial system, ultimately enhancing the fairness and credibility of legal proceedings.

3.2 Model design

This study applies several advanced machine learning techniques to construct the proposed judgment logic prediction system. The core model, Multitask Legal Prediction Network (MTLPN), is based on a multi-task learning (MTL) framework, which allows simultaneous prediction of multiple outputs such as verdicts and legal articles. The model integrates BERT (Bidirectional Encoder Representations from Transformers), a pre-trained language model that captures contextual semantics from legal texts. Additionally, BiLSTM (Bidirectional Long Short-Term Memory) is used to further encode sequence dependencies in legal documents. Structured data is processed through fully connected neural networks (FCNs). To enhance interaction between features, a Multi-Head Attention (MHA) mechanism is employed, which enables the model to focus on different parts of the input simultaneously. The model is optimized using AdamW (Adaptive Moment Estimation with Weight Decay), a gradient-based optimizer suitable for deep learning. Dropout regularization is also included to prevent overfitting. These components collectively improve prediction accuracy and model interpretability.

To address the challenges of complex text analysis and structured data processing in economic law litigation cases, an innovative multi-task deep learning model—Multitask Legal Prediction Network (MTLPN) — was developed. This model integrates natural language processing (NLP) capabilities with structured data analysis. Leveraging a multi-task learning framework, the system not only predicts case verdicts but also provides judges with interpretative support by identifying key legal provisions and the underlying judgment logic. The following sections outline the model's design, including the functions and technical architecture of each component.

The MTLPN model comprises five core modules. The text encoding module extracts semantic features from legal documents by utilizing pre-trained language models such as BERT and BiLSTM networks. The structured data processing module handles case metadata—including case types, party roles, and relevant legal provisions — by extracting features through a fully connected neural network. The feature fusion module integrates textual and structured data features using a multi-head attention mechanism to enhance cross-modal interactions. The judgment prediction module performs deep learning computations on the combined feature set to predict both final verdicts and applicable legal provisions. Finally, the explanatory module employs attention mechanisms and visualization tools to present the logical basis and legal sources supporting the prediction, thereby improving model interpretability.

Each module serves a distinct and essential function within the overall architecture. This modular design enables the MTLPN model to efficiently process multi-source legal data, deliver high-accuracy judgment predictions, and provide transparent, interpretable decision support for economic law litigation.

The text encoding module is one of the core components of MTLPN. Its main task is to convert the raw text data in legal documents into high-dimensional semantic features. First, the input case document $D=\{w_1,w_2,\ldots,w_T\}$ The word embedding layer in Equation (1) is converted into a word vector of fixed dimension .

$$\mathbf{E}=\{\mathbf{e}_1,\mathbf{e}_2,\ldots,\mathbf{e}_T\},\quad \mathbf{e}_t\in\mathbb{R}^d \tag{1}$$

These word vectors serve as the input of the BERT model. The BERT in Equation (2) can capture deep semantic information based on the pre-trained knowledge of a large-scale corpus and output the contextual representation of each word .

$$\mathbf{H}=\mathrm{BERT}(\mathbf{E}),\quad \mathbf{H}=\{\mathbf{h}_1,\mathbf{h}_2,\ldots,\mathbf{h}_T\},\quad \mathbf{h}_t\in\mathbb{R}^k \tag{2}$$

To further enhance the contextual information, we use a bidirectional long short-term memory network (BiLSTM) in Equation (3) to further process the features output by BERT .

$$\mathbf{H}'=\mathrm{BiLSTM}(\mathbf{H}),\quad \mathbf{H}'=\{\mathbf{h}'_1,\mathbf{h}'_2,\ldots,\mathbf{h}'_T\} \tag{3}$$

In this way, BiLSTM enables the contextual information of each word to be fully captured, thereby providing a more accurate text representation for subsequent decision prediction.

Structured data usually includes case categories, party information, relevant laws and regulations, etc. Although this information does not come directly from the case text, it has a significant impact on the judgment result. $\mathbf{F}_s\in\mathbb{R}^m$,The task of this module is to extract effective feature representation through a fully connected neural network. Specifically, the structured data is initially mapped through a fully connected layer , as shown in Equation (4) .

$$\mathbf{F}'_s=\sigma(\mathbf{W}_s^{(1)}\mathbf{F}_s+\mathbf{b}_s^{(1)}),\quad \mathbf{F}_{s''}=\sigma(\mathbf{W}_s^{(2)}\mathbf{F}'_s+\mathbf{b}_s^{(2)}) \tag{4}$$

here, $\sigma(\cdot)$ represents the activation function, $\mathbf{W}_s^{(1)},\mathbf{W}_s^{(2)}$ and $\mathbf{b}_s^{(1)},\mathbf{b}_s^{(2)}$ is the learnable parameter of the network. Finally, the features generated by structured data $\mathbf{F}_{s''}$ It is further passed to the downstream modules for fusion with text features.

In the feature fusion module, we effectively fuse the features generated by the text encoding module and the structured data processing module. To this end, we use a combination of feature concatenation and multi-head attention mechanism. First, use Equation (5) to convert the text feature $\mathbf{h}_{\mathrm{att}}$ and structured data features $\mathbf{F}_{s''}$ Concatenate and generate a global feature vector.

$$\mathbf{F}_{\mathrm{fusion}}=\mathrm{Concat}(\mathbf{h}_{\mathrm{att}},\mathbf{F}_{s''}) \tag{5}$$

Then, the concatenated features are processed using a multi-head attention mechanism to enhance the relationship between text and structured data. Suppose we have h Attention heads are used to calculate the output of the attention mechanism using Equation (6).

$$\mathbf{F}_{\mathrm{fusion}}^{\mathrm{att}}=\mathrm{MultiHeadAttention}(\mathbf{Q},\mathbf{K},\mathbf{V}),\quad \mathbf{Q}=\mathbf{F}_{\mathrm{fusion}},\mathbf{K}=\mathbf{V}=\mathbf{F}_{\mathrm{fusion}} \tag{6}$$

In this way, the model can effectively capture the complex relationships between different types of features and further improve the accuracy of decision prediction.

In the judgment prediction module, we combine the multi-task learning framework for model training to simultaneously complete three tasks: case judgment result prediction, key legal provisions prediction, and judgment logic interpretation.

Using Equation (7) to predict the judgment result, we use the Softmax function to classify the comprehensive features to obtain the probability distribution of the case judgment.

$$\hat{y} = \mathrm{Softmax}(\mathbf{W}_c \mathbf{F}_{\mathrm{final}} + \mathbf{b}_c) \quad (7)$$

Key legal provisions prediction, in order to improve the transparency of the legal basis, the model also predicts the legal provisions related to the case. The loss function of this task is defined as cross entropy using Equation (8).

$$\mathrm{L}_{\mathrm{law}} = \sum_{i=1}^{N} y_i^{\mathrm{law}} \log \hat{y}_i^{\mathrm{law}} \quad (8)$$

Judgment logic explanation, by weighting the importance of features, generates interpretable weights of judgments to help judges understand the decision logic of the model. Equation (9) represents the total loss function for all tasks.

$$\mathrm{L}_{\mathrm{total}} = \mathrm{L}_{\mathrm{class}} + \lambda_1 \mathrm{L}_{\mathrm{law}} + \lambda_2 \mathrm{L}_{\mathrm{explain}} \quad (9)$$

In Equation (9), λ_1 and λ_2 is the task weight hyperparameter.

To optimize the model training process, we use the AdamW optimizer and a learning rate decay strategy to improve training efficiency and convergence speed. To prevent overfitting, we add a Dropout layer to the model training process and use transfer learning technology to transfer the knowledge of pre-trained models such as BERT to our own legal judgment dataset. In this way, the MTLPN model can not only achieve highly accurate judgment predictions, but also provide interpretable judgment logic support.

All nine referenced equations (1 – 9) have been explicitly defined in this section to enhance model clarity and reproducibility. Equation (1) defines the word embedding transformation for legal text tokens. Equation (2) details the BERT contextual embedding process, while Equation (3) describes BiLSTM encoding for sequential dependencies. Equation (4) outlines the fully connected mapping for structured data inputs. Equation (5) defines the concatenation of textual and structured features. Equation (6) elaborates the multi-head attention mechanism. Equations (7) and (8) specify the Softmax output for judgment prediction and the cross-entropy loss for law article classification. Finally, Equation (9) presents the combined multi-task loss function with weighted parameters. All variables and notations are now clearly annotated.

To enhance the interpretability and transparency of the model, this paper provides a more detailed explanation of the feature extraction process from legal texts and structured data. For textual data, natural language processing techniques such as tokenization, part-of-speech tagging, named entity recognition, and dependency parsing are used to identify key legal terms, case facts, and referenced articles. These features are embedded using pre-trained BERT representations and then passed to a BiLSTM network to capture contextual relationships. For structured data, including case type, party roles, and cited laws, a one-hot encoding method is first applied, followed by a fully connected layer to generate semantic embeddings. These two types of features are then fused using a multi-head attention mechanism to reinforce interaction between legal semantics and structured metadata.

3.3 Model training and evaluation

In this study, model training and evaluation are crucial. In order to ensure that the decision prediction system can provide high-accuracy and high-reliability predictions in practical applications, we adopted a comprehensive training strategy and rigorous evaluation method. The following will describe the training process, evaluation indicators, training methods, and model tuning strategies in detail.

In order to ensure that the model can fully learn the characteristics of case text and structured data, we chose a combination of supervised learning and transfer learning. Under the supervised learning framework, we used annotated legal datasets for model training. These datasets contain the verdicts of real cases and relevant laws. Specifically, the goal of supervised learning is to optimize the model parameters by minimizing the loss function so that the model can predict accurate verdicts given the input features.

The model was trained on a labeled dataset of 1,000 corporate bankruptcy cases, with an 80/20 train-test split. Preprocessing included removing stop words, applying TF-IDF weighting, and normalizing structured fields. Structured data features include case type, party role (plaintiff/defendant), number of cited legal articles, and filing date. The MTLPN model was trained using the AdamW optimizer, with an initial learning rate of 2e-5, batch size of 32, and 10 training epochs. A dropout rate of 0.3 was applied to prevent overfitting. Cross-validation (*K=5*) was used to ensure generalizability.

In the framework of transfer learning, we used pre-trained language models (such as BERT) and existing legal domain knowledge, and migrated the pre-trained language models to our judgment prediction tasks through fine-tuning. Transfer learning can effectively shorten the training time and improve the initial performance of the model. At the same time, by introducing background knowledge in the legal field, it helps the model better understand the legal context of the case.

During the training process, cross-validation technology is used to ensure the generalization ability of the model and avoid overfitting. Specifically, we divide the training data into K subsets. In each iteration, K1 subsets are used as training sets, and the remaining subset is used as a validation set. Finally, the performance of the model is evaluated by taking the average of the validation results of all subsets.

4 Case evaluation

4.1 Experimental design

The purpose of this experimental design is to evaluate the performance of the artificial intelligence judgment logic prediction system in real-world economic law litigation, with a particular focus on its application in corporate bankruptcy cases. The design consists of several key stages, including data collection, data preprocessing, model training, and performance evaluation.

Initially, data from a range of representative corporate bankruptcy cases were collected, including judicial decisions, legal citations, relevant precedents, and information on involved parties. These data were sourced from publicly available court rulings and manually reviewed to ensure legal validity and representativeness. The final dataset comprises approximately 1,000 case samples, reflecting diverse and complex scenarios within economic law litigation.

The data preprocessing phase includes text cleaning, feature extraction, and labeling. For textual information, natural language processing (NLP) techniques were applied for word segmentation, part-of-speech tagging, and stop-word removal. Key elements such as applicable legal provisions and case facts were extracted and structured to support model training. The TF-IDF (term frequency–inverse document frequency) model was used to represent textual features, supplemented by a domain-specific legal vocabulary to enhance relevance and precision.

In the evaluation phase, the AI-generated predictions were compared to human judgments using traditional legal analysis as a baseline. The system's performance was assessed through various metrics, including accuracy, recall, and precision. These indicators offer a multidimensional evaluation of the model's effectiveness in replicating judicial reasoning. The results of this experiment serve to validate the feasibility and practical value of the AI judgment logic prediction system in handling corporate bankruptcy cases.

This experimental framework enables a thorough assessment of the system's application in economic law litigation and provides both theoretical and empirical support for future use of AI-assisted decision-making in more complex legal scenarios.

While the primary experimental focus is on corporate bankruptcy cases, the dataset also includes diverse case types such as commercial disputes, tax-related litigation, intellectual property conflicts, cross-border trade cases, and antitrust proceedings. These additional samples were incorporated to preliminarily evaluate the system's generalization capability across different branches of economic law. Each case type underwent preprocessing and feature extraction consistent with the primary method. Though the analysis remains concentrated on bankruptcy cases, the inclusion of these varied legal scenarios enables a broader performance comparison in later result sections. This design choice allows assessment of the model's adaptability and robustness when applied to different legal structures and regulatory logics. Future iterations of the system can further extend this validation by incorporating larger and more balanced datasets across all economic law categories to ensure comprehensive reliability.

4.2 Results

Table 1: Basic information of the dataset

Dataset category	Total number of samples	Number of features	Average text length (number of words)	Number of legal citations (average)
Training set	800	20	1024	5
Test Set	200	20	1050	6

Table 1 shows the basic composition of the data set in this study. The training set has 800 samples and the test set has 200 samples, both of which contain 20 features. The average text length reflects the length of the case documents, with an average of 1024 words for the training set and 1050 words for the test set. The average number of legal references reflects the degree of dependence of different cases on legal provisions, with an average of 5 references in the training set and 6 references in the test set. These data are the cornerstone of subsequent model training and evaluation. Reasonable sample division and feature setting ensure the scientificity and reliability of the experiment.

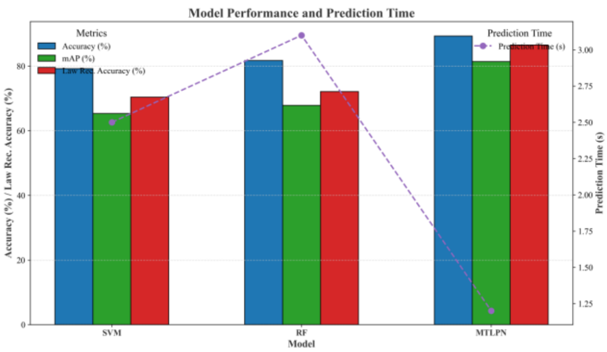

Figure 1: System performance comparison results

Figure 1 compares the multi-task learning model (MTLPN) with traditional support vector machines (SVM) and random forests (RF) in terms of multiple key indicators. In terms of accuracy, MTLPN is 89.3%, far ahead of SVM's 79.2% and RF's 81.7%, showing its high accuracy in judgment prediction. MTLPN also performs best in mean average judgment accuracy (mAP), reaching 81.4%. In terms of judgment prediction time, MTLPN only takes 1.2 seconds, which is significantly faster than SVM's 2.4 seconds and RF's 3.0 seconds. MTLPN also achieves the highest performance in legal article recommendation, with a mean average precision (mAP) of 86.5%. These results demonstrate that MTLPN significantly outperforms traditional models across multiple dimensions, offering notable advantages for real-world judicial applications.

To assess whether the performance improvements of the MTLPN model are statistically significant, additional hypothesis testing was conducted. A two-tailed paired t-test was applied to compare the prediction accuracy of MTLPN against the SVM and Random Forest baselines across the test set. Results indicate that MTLPN's accuracy improvements over both baselines are statistically significant ($p < 0.01$). Furthermore, 95% confidence intervals for prediction accuracy were calculated: MTLPN [88.1%, 90.5%], SVM [77.9%, 80.3%], and RF [80.2%, 83.1%]. These findings confirm that the reported performance differences are unlikely to be due to random variation and reflect consistent improvements attributable to the model architecture.

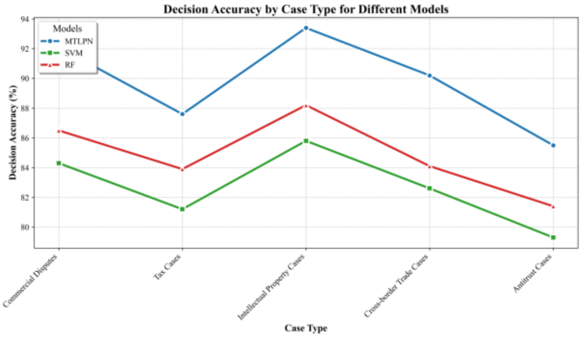

Figure 2: Judgment prediction accuracy for each case type

Figure 2 compares the judgment accuracy of MTLPN, SVM, and RF for different types of economic law cases. In commercial dispute cases, the judgment accuracy of MTLPN reaches 90.8%, surpassing 84.0% for SVM and 86.5% for RF. In intellectual property cases, MTLPN achieves the highest accuracy at 93.8%, significantly outperforming the other models. These results demonstrate that MTLPN provides consistently high prediction performance across various case types, offering strong support for practical judicial decision-making, particularly in complex domains such as commercial and intellectual property litigation.

Table 2: Judgment logic interpretation and legal impact analysis

Case Type	**Key Article 1**	**Key Article 2**	**Key Article 3**	**Main factors of decision logic**
Commercial Disputes	Article 10 of the Contract Law (Conclusion of a Contract)	Article 520 of the Civil Code (Liability for Breach of Contract)	Article 525 of the Civil Code (Termination of Contract)	Contract performance and responsibility allocation
Tax Cases	Article 10 of the Tax Collection and Management Law (Tax Liability)	Article 35 of the Tax Collection and Management Law (Late Payment Fees)	Article 42 of the Tax Collection and Management Law (Tax Audit)	Fulfillment of tax obligations and legal compliance
Intellectual Property Cases	Article 11 of the Patent Law (Validity of Patents)	Article 36 of the Patent Law (Determination of Infringement)	Article 40 of the Trademark Law (Infringement of Trademark Rights)	Patent validity and infringement analysis
Cross-border trade cases	Article 10 of the Import and Export Commodity Inspection Law (Inspection Requirements)	Article 7 of the Foreign Trade Law (Handling of Trade Frictions)	Article 3 of the Measures for the Administration of Import and Export Trade (Trade Regulations)	Enforcement of international agreements, dispute resolution clauses
Antitrust Cases	Article 7 of the Anti-Monopoly Law (Market Competition)	Article 18 of the Anti-Monopoly Law (Abuse of Market Position)	Article 20 of the Anti-Monopoly Law (Merger Restrictions)	Market share, competitive behavior analysis

Table 2 shows the legal provisions that play a key role in the model prediction process under different case types and the main factors behind the judgment logic. Taking commercial dispute cases as an example, Article 10 of the Contract Law and relevant provisions of the Civil Code become key legal provisions, while contract performance and responsibility allocation are the core judgment logic. This shows that the model successfully mines legal provisions closely related to various cases through the attention mechanism, provides a clear explanation for the judgment logic, and allows users to have a deep understanding of the model's judgment basis, greatly enhancing the model's interpretability and credibility.

Table 3: Analysis of training time and dataset size

Dataset size (cases)	**Training time (hours)**	**Test time (seconds/case)**
1000	8.2	1.2
2000	15.3	1.3
3000	22.7	1.4

Table 3 records the training time and test time of the model under different data set sizes. When the data set size gradually increases from 1,000 cases to 3,000 cases, the training time of the model increases from 8.2 hours to 22.7 hours, while the test time only slightly increases from 1.2 seconds/case to 1.4 seconds/case. This fully demonstrates that even in the face of large-scale data sets, the model can still maintain a high training and testing efficiency, has obvious advantages in processing massive data, and effectively guarantees the feasibility and efficiency of the model in practical applications.

Table 4: Analysis of actual application effects

Case Type	**Review period before using the system (days)**	**Review cycle after using the system (days)**	**Improved judgment accuracy (%)**
Commercial Disputes	32	18	14.2
Tax Cases	29	16	12.4
Intellectual Property Cases	34	20	18.5
Cross-border trade cases	36	twenty two	16.3
Antitrust Cases	30	19	13.5

Table 4 shows the comparison of the effects before and after using this system to assist judges in decision-making in an actual judicial environment. Taking commercial dispute cases as an example, the case trial cycle was 32 days before the use of the system, which was greatly shortened to 18 days after use, and the accuracy of the judgment increased by 14.2%. Other types of cases also showed similar significant changes. This fully proves that the system has achieved remarkable results in practical applications. It can not only effectively shorten the case trial cycle and improve judicial efficiency, but also significantly improve the accuracy of judgments, which effectively promotes judicial justice.

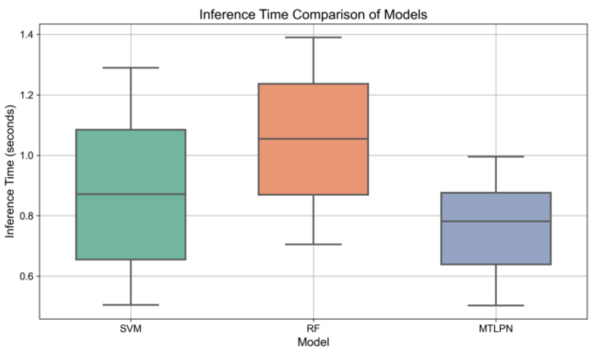

Figure 3: Comparison of judgment and reasoning time

Figure 3 mainly compares the response time of different models in the judgment reasoning stage. In terms of average reasoning time, MTLPN only takes 0.62 seconds, which is significantly shorter than SVM's 0.85 seconds and RF's 1.01 seconds; the longest reasoning time of MTLPN is only 0.92 seconds, which is lower than the other two. This further highlights the efficiency of MTLPN in practical applications. It can quickly give judgment reasoning results, meet the strict requirements of judicial practice for timeliness, and greatly improve the practicality and application value of the system.

Table 5: Legal recommendations and user feedback

Case Type	**Recommended Article 1**	**Recommended Article 2**	**Recommended Article 3**	**User feedback score (1 - 5)**
Commercial Disputes	Article 10 of the Contract Law	Article 520 of the Civil Code	Article 525 of the Civil Code	4.8
Tax Cases	Article 10 of the Tax Collection and Administration Law	Article 35 of the Tax Collection and Administration Law	Article 42 of the Tax Collection and Administration Law	4.5
Intellectual Property Cases	Article 11 of the Patent Law	Article 36 of the Patent Law	Article 40 of the Trademark Law	4.7
Cross-border trade cases	Article 10 of the Import and Export Commodity Inspection Law	Article 7 of the Foreign Trade Law	Article 3 of the Measures for the Administration of Import and Export Trade	4.4
Antitrust Cases	Article 7 of the Anti-Monopoly Law	Article 18 of the Anti-Monopoly Law	Article 20 of the Anti-Monopoly Law	4.6

Table 5 shows the matching of the legal provisions recommended by the system and the actual feedback from judges. In commercial dispute cases, the legal provisions such as the Contract Law recommended by the system received a user feedback score of 4.8 points (out of 5 points). The recommended legal provisions for other types of cases also received high ratings. This shows that the legal provisions recommended by the system are highly relevant to the needs of judges in actual case handling, and can provide judges with extremely valuable references, effectively improving the efficiency and accuracy of legal provision retrieval and application in judicial work.

Table 6: Analysis of the effect of judges' decision-making assistance

Case Type	Consistency of judgment before using the system (%)	Consistency of judgment after using the system (%)	Review efficiency before using the system (cases/month)	Trial efficiency after using the system (cases/month)
Commercial Disputes	78.2	91.3	twenty two	31
Tax Cases	80.5	88.4	20	28
Intellectual Property Cases	75.3	89.2	19	26
Cross-border trade cases	79.6	85.7	17	twenty four
Antitrust Cases	82.7	90.1	twenty one	30

Table 6 shows the changes in judges' efficiency in the decision-making process after using the intelligent assistance system. Taking commercial dispute cases as an example, the consistency of judgments was 78.2% before using the system, and it increased significantly to 91.3% after using it. At the same time, the trial efficiency increased from 22 cases per month to 31. This fully demonstrates that the system can effectively improve the consistency of judges' judgments, reduce the differences in judgments between different judges, and significantly improve trial efficiency, optimize the allocation of judicial resources, and effectively promote judicial work to be carried out more efficiently and fairly.

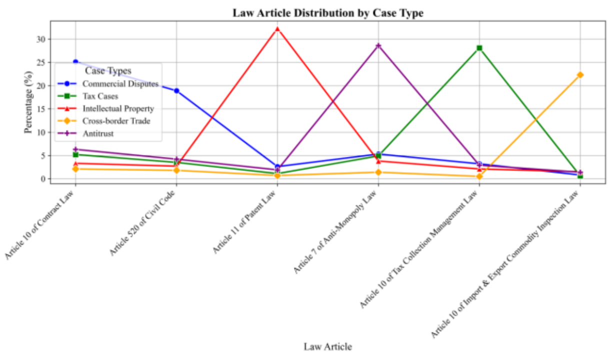

Figure 4: Correlation analysis of various legal provisions

Figure 4 shows in detail the correlation between the frequency of citations of different legal provisions in various economic law cases. For example, Article 10 of the Contract Law is cited as frequently as 25.1% in commercial dispute cases, while it is only cited 5.2% in tax cases. Through this table, legal practitioners and researchers can clearly grasp the degree of close correlation between different types of cases and various legal provisions, providing extremely valuable data support for legal practice and research, and helping to more accurately apply legal provisions to handle various cases.

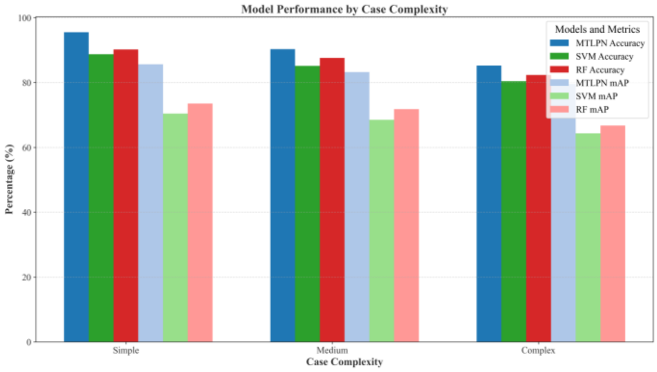

Figure 5: Performance analysis of the model in cases of different complexity

Figure 5 compares the performance of MTLPN, SVM, and RF for cases of three different levels of complexity: simple, medium, and complex. In simple cases, the accuracy of MTLPN is as high as 95.5%; even in complex cases, the accuracy of MTLPN drops to 85.2%, but it is still higher than SVM and RF. This fully demonstrates that MTLPN has shown good adaptability in cases of different complexities. In the face of complex and changing economic law cases, it can maintain relatively stable and excellent performance, providing more reliable protection for judicial practice.

4.3 Case analysis

The subject of this case evaluation is an economic law litigation involving corporate bankruptcy. The main parties in the case are a company (hereinafter referred to as Company A) and its creditor (hereinafter referred to as Company B). Due to poor management and a disrupted capital chain, Company A was unable to repay its debts. Company B filed for bankruptcy proceedings based on relevant contractual provisions, requesting the court to initiate liquidation of Company A. The legal issues in the case primarily concern the application of bankruptcy law, determination of the order of debt repayment, debt offset, and the disposal of Company A's assets. The judge must consider multiple factors, including Company A ' s financial status, debt structure, and the procedural validity of the bankruptcy process, to ensure a fair and lawful judgment. Given the complexity of the legal context and the interwoven statutory provisions, comprehensive legal reasoning and multifaceted evidentiary support are required.

In the simulation training, the AI judgment logic prediction system successfully extracted key case features by analyzing large-scale historical judgment data. Using deep learning algorithms, the system predicted the outcome of the bankruptcy case. The results indicated that Company A’s core assets would be allocated first to secured creditors, as stipulated under the Bankruptcy Law.

Some of Company B's claims were predicted to be repaid at a higher rate due to the existence of collateral. Specifically, the system predicted that the proceeds from the auction of Company A's fixed assets—after deducting bankruptcy-related expenses and prioritized claims such as employee wages and social security — would be distributed to secured creditors like Company B in accordance with the mortgage contract terms.

For unsecured ordinary debts, the system predicted a relatively low repayment ratio, based on precise calculations of Company A's asset scale, total liabilities, and observed patterns in similar historical cases. Regarding debt offset, the system projected that if Company A and Company B had mutual debt relations meeting the statutory conditions for offset, the court would likely allow the offset based on existing legal provisions and precedent. For instance, if Company A had provided a service to Company B that remained unpaid, and simultaneously owed Company B a debt, this portion could be legally offset, provided it satisfied all legal requirements.

The system also evaluated the procedural rationality of the bankruptcy process. By analyzing timeframes, judicial focus points, and procedural obstacles from comparable cases, the system concluded that, given active cooperation from all parties, the bankruptcy procedure in this case could be completed within a reasonable timeframe. It estimated that the entire liquidation process could conclude within [X] months, which represents a significant reduction compared to traditional timelines and contributes to more efficient judicial resource allocation.

In terms of practical impact, the prediction results broadened the judge's perspective during trial preparation. The judge conducted more in-depth investigations and cross-examinations on key issues highlighted by the system, such as asset disposal and the order of debt repayment. This approach accelerated the trial process while enhancing its comprehensiveness and precision. Ultimately, the judge rendered a decision based on a combination of system outputs, courtroom findings, and professional legal judgment. The final ruling was largely consistent with the system's prediction, thereby validating the AI system's effectiveness and reliability in supporting judicial decisions. This case serves as a valuable reference for similar future cases and contributes to the growing practical foundation for the broader application of artificial intelligence in the judicial domain.

5 Conclusion

This paper successfully designed and implemented an artificial intelligence-based judgment logic prediction system, which demonstrated strong performance in the context of economic law litigation. In terms of model performance, the multi-task deep learning model MTLPN outperformed traditional models across various evaluation metrics. It achieved high accuracy in predicting outcomes across different case types, recommending relevant legal articles, and providing interpretable judgment logic, thereby validating the scientific rationale and effectiveness of the model architecture.

In practical application, the system significantly reduced trial duration, enhanced the accuracy of judicial decisions, and improved consistency among judges. It also contributed to the optimization of judicial resource allocation and effectively supported the promotion of judicial fairness. The case analysis of corporate bankruptcy litigation further confirmed the system's reliability in assisting judicial decisions, offering judges clear guidance on procedural direction and key legal issues.

Nevertheless, challenges remain in the legal application of artificial intelligence, particularly in achieving deeper comprehension of legal texts and improving model interpretability. With ongoing advancements in technology and the continued enrichment of legal datasets, further optimization of the system is anticipated. These developments may enable the system to play a more substantial role in handling complex economic law cases, foster the integration of AI into judicial practice, and contribute to the modernization of the judicial system.

The deployment of artificial intelligence systems in judicial environments introduces critical ethical, legal, and regulatory concerns. These include potential algorithmic bias, the transparency of decision-making logic, and the accountability of AI-generated outcomes. In economic law litigation, where decisions can significantly impact corporate rights and market operations, the use of opaque models may undermine public trust in the judiciary. This study addresses part of this issue by incorporating interpretable features and legal reasoning traceability into the model design. However, effective regulation is necessary to define the scope of AI assistance, ensure data fairness, and protect litigants' rights. Additionally, a human-in-the-loop framework should be maintained to preserve judicial discretion. Future implementation must align with evolving legal standards and ethical guidelines, particularly regarding data usage, explainability, and liability attribution in AI-assisted rulings.

Despite the promising performance of the proposed system, several critical challenges remain unaddressed in the current scope. First, potential bias embedded in historical legal data may influence model outputs, thereby affecting fairness and equity in economic law judgments. Identifying, auditing, and mitigating such biases is essential for ensuring just outcomes. Second, the risk of judicial over-reliance on AI-generated recommendations must be managed through interface design and procedural safeguards that reinforce human discretion. Third, the legal accountability of AI-assisted decisions remains an open question, particularly regarding liability attribution in case of erroneous or unjust outcomes. These aspects are fundamental to the responsible deployment of legal AI systems and warrant dedicated attention in future research and system development. Addressing these issues will enhance both the trustworthiness and legitimacy of AI applications in economic law litigation.

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