

Retraction

Retracted: The Legal Regulation of Artificial Intelligence and Edge Computing Automation Decision-Making Risk in Wireless Network Communication

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] J. Sun, "The Legal Regulation of Artificial Intelligence and Edge Computing Automation Decision-Making Risk in Wireless Network Communication," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 1303252, 13 pages, 2022.

Research Article

The Legal Regulation of Artificial Intelligence and Edge Computing Automation Decision-Making Risk in Wireless Network Communication

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This article is aimed at studying the legal regulation of artificial intelligence and edge computing automated decision-making risks in wireless network communications. The data under artificial intelligence is full of flexibility and vitality, which has changed the way of data existence in the whole society. Its core is various algorithm programs, which determine the existence of artificial intelligence. In this environment, society develops rapidly with unstoppable momentum. However, from a legal perspective, artificial intelligence has algorithmic discrimination, such as gender discrimination, clothing discrimination, and racial discrimination. It does not possess openness, objectivity, and accountability. The consequences are sometimes serious enough to endanger the public interest of the entire society, leading to market disorder, etc. Therefore, the problem of artificial intelligence algorithm discrimination remains to be solved. This article uses algorithms to adjust algorithm discrimination to reduce the harm caused by artificial intelligence algorithm discrimination to a certain extent. First of all, this article introduces a regulatory-based edge cloud computing architecture model. It is mentioned that distributed cloud computing can use subsystems to calculate various resources and storage resources and can make automated decisions when calculating certain data. In order to reduce the impact of algorithm discrimination and trigger data diversification to reduce the probability of discrimination, an edge computing network data capture system is designed. And this article mentions the BP neural network model. The BP neural network model is divided into input layer, output layer, and hidden layer. The training samples are passed from the input layer to the output layer through the hidden layer. If the output information does not meet expectations, the error will be back-propagated, and the connection weight will be adjusted continuously. This paper proposes a deep learning system model in real-time artificial intelligence driven by edge computing. When this model is applied to legal regulations, it can cooperate with edge computing and artificial intelligence algorithms to provide high-precision automated decision-making. Finally, this paper designs an artificial intelligence-assisted automated decision-making experiment based on the theory of legal computing. This paper proposes a Bayesian algorithm that uses edge algorithms to merge into artificial intelligence and verifies the feasibility of this hypothesis through experiments. The experimental results show that it has a certain ability to regulate algorithmic discrimination caused by artificial intelligence in legal regulations. It can improve the regulatory effects of laws and regulations to a certain extent, and the improved artificial intelligence Bayesian algorithm clustering effect of edge computing is increased by about 7.2%.

1. Introduction

1.1. Background. The field of artificial intelligence in the time stream is developing rapidly, and various fields have made great strides with artificial intelligence technology. Artificial intelligence has also provided varying degrees of help to

the transformation and progress of human society. However, behind the development of artificial intelligence, there are also various issues that cannot be ignored, whether the technology should first follow the procedural rules or legal ethics. No matter what kind of technology it is, it will have its shortcomings, and in artificial intelligence algorithms, there is

also algorithm discrimination. This kind of algorithm will lead to unreasonable and legal and ethical consequences under various artificial intelligence data analysis. Data-driven has caused algorithmic discrimination. Algorithm discrimination occurred during the interaction. Artificial intelligence systems have generated algorithmic discrimination in order to achieve user needs. Algorithmic discrimination is not an exception. The image software developed by Google mistakes black people in pictures for gorillas. Such discrimination is extremely unreasonable and unethical. The chat bot Tay developed by Microsoft has made similar mistakes. Under the wrong guidance of human beings and learning cognition based on wrong data, Tay has become a bad artificial intelligence that is sexist and antisemitic. As a program that assists humans, algorithms must not only comply with their own rules but also be based on legal data. The necessary legal intervention can make the route of artificial intelligence more reasonable. Therefore, in the era of artificial intelligence, it is very important to solve the problem of algorithm discrimination, not only to find a suitable solution but also to specify detailed and reasonable rules. First of all, it is necessary to conduct stronger institutionalized management of algorithms and strictly review them. Second, the relevant practitioners and companies in the industry must be solemnly informed and regulated in terms of law, ethics and ethics. Third, the implementation of this measure requires several strong players in the industry to take the lead in implementing it, and then, it is possible to obtain actual results. Finally, the process of algorithm development and design is particularly critical, so the technique of optimizing the algorithm is a crucial step. This article uses algorithms to reduce algorithm discrimination, based on edge computing in artificial intelligence and Bayesian decision theory, and discusses how to reduce artificial intelligence algorithm discrimination in law.

1.2. Significance. This article uses artificial intelligence to automate the decision-making of legal regulations, but there are many misinformation and misjudgments in artificial intelligence's automated decision-making. Therefore, this article is committed to reducing the algorithm discrimination brought by artificial intelligence and proposes to use edge algorithms to optimize the Bayesian algorithm to improve its clustering ability. It can better judge the data feature set and make more precise divisions to improve the winning rate in legal cases. And it uses artificial intelligence decision trees for classification processing. Through the comparison of the case's winning rate, Bayesian algorithm and edge computing fusion of Bayesian algorithm purity, RI index, and data clustering before and after data clustering, the experimental conclusions are drawn. Finally, a questionnaire survey is conducted to analyze the actual feasibility, and it can be seen that the improvement of Bayesian decision theory by edge computing is indeed feasible, and the effect is more obvious. The probability of winning a case will be increased by 4.2% compared with purely human-handled cases and the clustering effect of the artificial intelligence Bayes algorithm improved by edge computing will be

increased by 7.2%. The practical and theoretical significance of the research results have been realized.

1.3. Related Work. This article is dedicated to explaining the research on the legal regulation of artificial intelligence and edge computing automated decision-making risks in wireless network communications. Hassabis et al. believes that the fields of neuroscience and artificial intelligence (AI) have a long and intertwined history, and a better understanding of biological brains can play a vital role in building artificial intelligence. And he investigated the historical interaction between AI and neuroscience and emphasized the current progress of AI inspired by neural computing research in humans and other animals [1]. Glauner et al. believe that NTL has caused significant damage to the economy. Because in some countries, they may account for 40% of the total electricity allocated. They use artificial intelligence (AI) to solve this problem. Promising methods fall into two categories: expert systems that combine handmade expert knowledge or machine learning, also known as pattern recognition or data mining. It can learn fraudulent consumption patterns from examples without explicit programming [2]. Taleb et al. said that multiaccess edge computing (MEC) is an emerging ecosystem that is aimed at converging telecommunications and IT services to provide a cloud computing platform at the edge of the radio access network (RAN). MEC provides storage and computing resources at the edge, reduces the delay of mobile terminal users, and makes more effective use of mobile backhaul and core networks [3]. Mao et al. have developed an online joint radio and computing resource management algorithm for the multiuser MEC system. The goal is to minimize the long-term average weighted sum power consumption stability constraint of the mobile device and the MEC server under the constraint of the task buffer. In each time slot, it obtains the best CPU-cycle frequency of the mobile device in a closed form and uses the Gauss-Seidel method to determine the best transmit power and bandwidth allocation for calculating offloading [4]. Zheng et al. proposed a fault variable identification method for multivariable/minor fault diagnosis. They take the deviation factor as the sample feature, use Bayesian decision theory to calculate the possibility of variable failure, and then use multidimensional reconstruction contribution (MRBC) to determine the failure source variable [5]. Biedermann et al. stated that forensic science and law have been discussing how to prove these conclusions and conclusion standards through rational argumentation, for example, fingerprints, handwriting checks, kinship analysis, or anthropology. The use of formal reasoning methods based on (Bayesian) decision theory is available in the literature, but at present such reference principles are not clearly used for operating evidence reports and subsequent decision-making [6]. But these studies all have more or less insufficient arguments.

1.4. Innovation. This article focuses on the research on the legal regulation of artificial intelligence and edge computing automated decision-making risks in wireless network communications. It precisely links edge computing with

Bayesian decision-making theory, improves the automated decision-making capabilities of artificial intelligence in legal regulation research, and reduces the risk of automated decision-making. It uses algorithms to adjust algorithm discrimination and to a certain extent reduces the harm caused by artificial intelligence algorithm discrimination. This paper proposes a regulatory-based edge cloud computing architecture model, BP neural network model, and edge computing-driven deep learning system model in real-time artificial intelligence. It provides high-precision automated decision-making with artificial intelligence. Finally, this article conducts artificial intelligence-assisted automated decision-making experiments based on the theory of legal computing. And this paper verifies that the Bayesian decision theory of edge computing hybrid artificial intelligence can effectively reduce the legal discrimination caused by artificial intelligence in legal cases.

2. Edge Computing and BP Neural Network Model

2.1. Regulatory-Based Edge Cloud Computing Architecture Model. Distributed cloud computing can make up for the shortcomings of the centralized cloud computing architecture. It uses subsystems to calculate various resources and storage resources and can make automated decisions when calculating certain data [7]. Distributed computing, also known as distributed computing, mainly studies how distributed systems perform calculations. A distributed system is a system formed by a group of computers that are connected to each other through the network to transmit messages and communications and coordinate their behaviors. Components interact with each other to achieve a common goal. Figure 1 shows the distributed cloud computing structure system:

This architecture has no hard requirements on the current network status. Users can be allocated to reduce network load and achieve data interaction to avoid excessive data transmission at the same time. The interaction methods are Ajax in native JS and Ajax in jQuery. It is quite flexible and can provide services according to user needs. It is equivalent to the parallel structure of circuits. When a subsystem fails, it does not affect the entire cloud computing environment, saves resources and can be reused [8]. However, there are restrictions in some places. For example, when laws and regulations are automatically integrated, they will be affected by the environment and the rate of use of regulations. It is difficult to cooperate with each other, relatively independent, and the security is not too high, and the system maintenance ability is weak [9]. At this time, for these shortcomings of distributed cloud computing, edge computing can be used to improve. By using the core cloud and edge cloud composition to coordinate system functions, Figure 2 shows the edge cloud computing architecture:

Using edge computing can well combine the advantages of the network structure, with high resource aggregation, convenient collaboration, and high resource utilization. When using edge computing for data collection, it is necessary to use various equipment to complete the process

through machine learning and artificial intelligence and other algorithms. It can prevent unfairness caused by algorithmic discrimination when making automated decisions on regulations, such as imbalance between men and women. Therefore, at this time, edge devices and sensors are used to collect data and preprocess the data to prevent excessive automation deviation. Correction, denoising, and windowing of data collected by artificial intelligence were done [10]. In preparing laws and regulations, information collection uses a distributed network data capture system. By building a network of edge devices, sensors are prepared to monitor the violation of the law in a certain place and analyze the factors and gender of the violation of the law. And in order to reduce the impact of algorithm discrimination, data was triggered diversification to reduce the probability of discrimination [11]. The information on the violation of laws and regulations by the edge computing network is shown in Figure 3.

Its advantages are not only reflected in physical distribution but also timeliness and flexibility. It has enough advantages to process data and feed it back to edge devices in time [12]. Edge computing must add or physically upgrade equipment for the organization to gain more computing power or storage space. It can be difficult to protect distributed edge computing networks. Edge computing requires more storage space and more maintenance than servers in data centers.

2.2. BP Neural Network Model. The basic fast-growing unit of the nervous system is the nerve cell, which has both dynamic and static characteristics, perfect and complex. Through the use of coupling and plasticity to form an organic whole, it produces memory and recognition processing for learning. The artificial neural network is the intelligent nervous system, which abstractly imitates the local nerves of the brain [13]. According to the classification of internal information flow and according to the network topology, it is classified as the most common artificial neural network model, which is divided into input layer, output layer, and hidden layer [14]. The signal through the input layer was activated, and then, the features through the hidden layer were extracted. Different hidden layer neural units correspond to different input layers with different neural unit weights and self-bias. The excitement of the input layer is transferred to the excitement of the hidden layer, and finally, the output layer outputs the result according to different hidden layer weights and self-bias. Figure 4 shows the hierarchical network structure:

Each neuron of the hierarchical network structure can correspond to the information of the previous layer, but each neuron of the same layer does not have a direct connection. The next one is that the neurons in the neural network can receive external input information and perform processing at the same time, that is, information loop processing can be performed [15]; the end of the training process is the end of the loop. When a certain value is reached, the input layer of the BP neural network cannot be entered, as shown in Figure 5.

Then, the BP neural network was shown in the artificial neural network. The learning algorithm of this neural

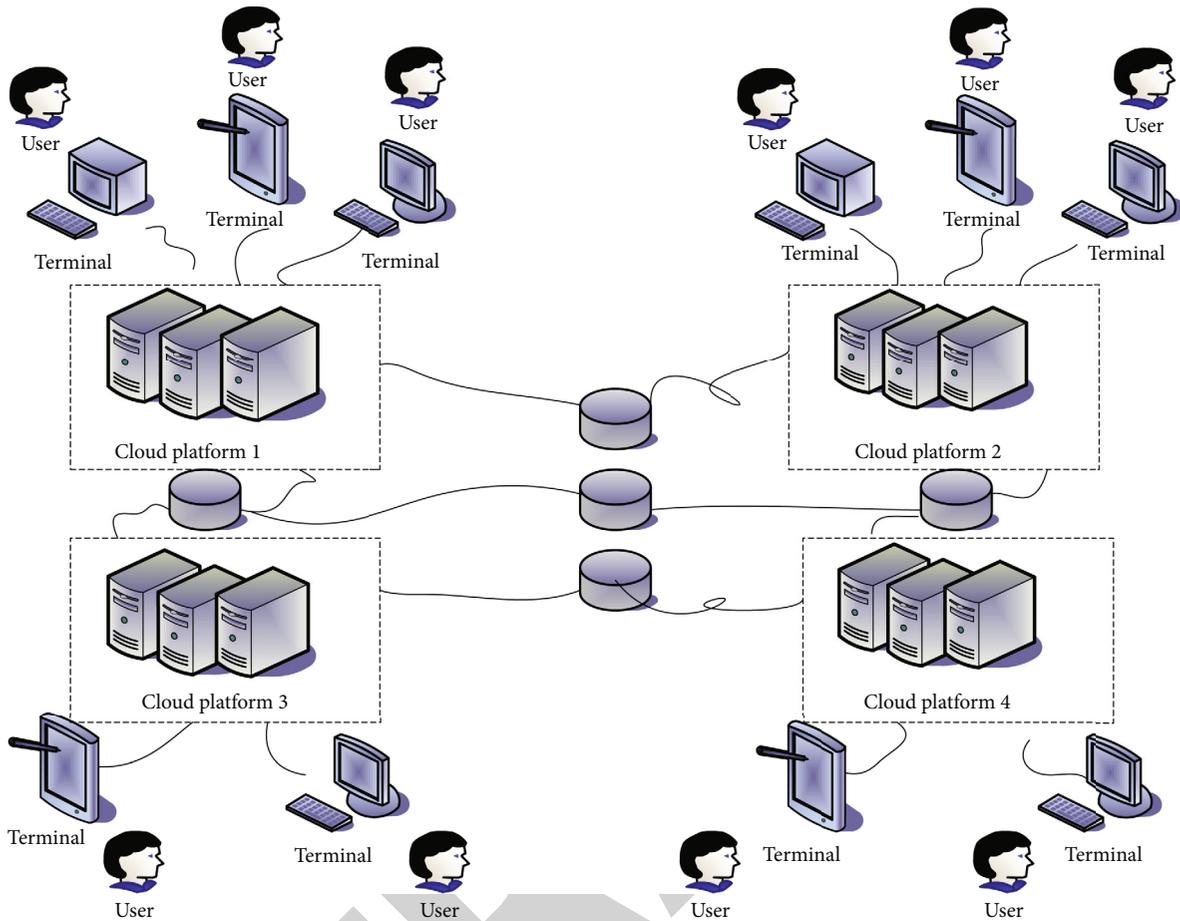


FIGURE 1: Distributed cloud computing architecture.

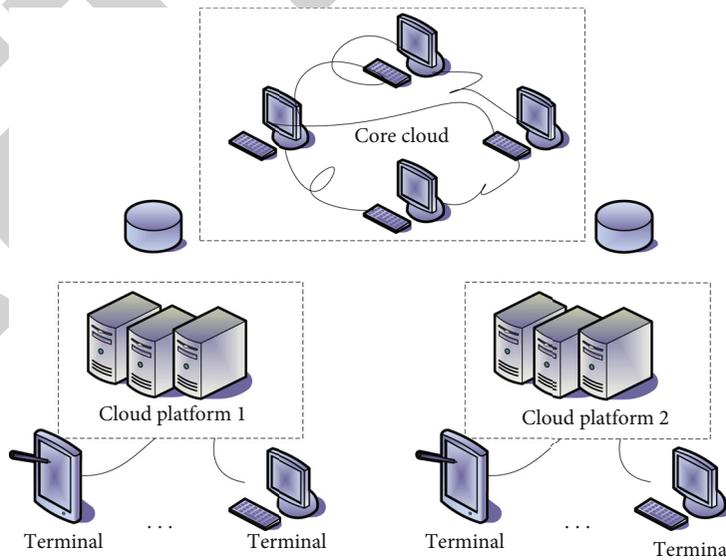


FIGURE 2: Edge cloud computing architecture.

network is a multilayer inverse method. Multilayer backstepping refers to the neural network through a chain method of derivation, step by step to propagate the error from back to

front, and the training samples are passed from the input layer to the output layer through the hidden layer. If the output information does not meet expectations, the error will be

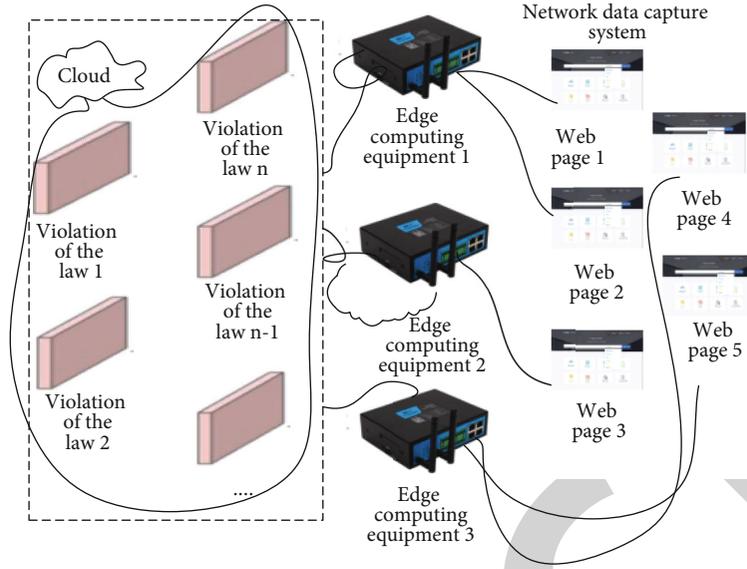


FIGURE 3: Edge computing network data capture.

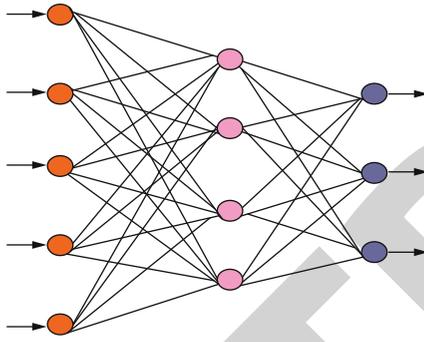


FIGURE 4: Hierarchical network structure.

back-propagated, and the connection weight will be adjusted continuously. It is the learning and training process of BP neural network, until the error is small enough or has reached the required preset value, the training process can be ended [16]. Figure 6 shows the BP neural network structure:

At this time, the input layer of the BP network is represented by m_k , and its actual output is represented by n_k . The expected output of the BP neural network is u_k , and the weight is Q_{kjt} . It means the value between the j th neuron of the k layer and the t th neuron of the $k+1$ layer. At the same time, O_{kj} is used to represent the j th neuron of the layer k , the threshold is ω_{kj} , the total input is net_{kj} , and the number of nodes is s_k . The forward propagation of the BP neural network can be obtained as

$$net_{kj} = \sum_{t=1}^{s_{k-1}} O_{(k-1)t} \cdot Q_{(k-1)tj} \quad (1)$$

$$O_{kj} = f_m(net_{kj}) = \frac{1}{1 + \exp[-(net_{kj} - \omega_{kj})]} \quad (2)$$

The back-off algorithm of the BP neural network takes the O_{kj} when the j neuron is in the output layer as the actual output and records it as n_k . The weight is adjusted by the error reversal between the actual output and the expected output. The error can be expressed as $x_j = u_j - n_j$, and the objective function is expressed as

$$x = \frac{1}{2} \sum_j (u_j - n_j)^2 \quad (3)$$

At this time, the weight of the BP neural network is corrected according to the direction of the error gradient.

$$\Delta Q_{kjt} = -\eta \frac{\lambda X}{\lambda Q_{kjt}} \quad (4)$$

η represents the learning efficiency of training parameters, and the value is between 0 and 1. The recurrence relationship between the neuron and the weight is calculated to directly program the program.

$$\Delta Q_{kjt} = -\eta \frac{\lambda X}{\lambda Q_{kjt}} = -\eta \frac{\lambda X}{\lambda net_{(k+1)t}} \cdot \frac{\lambda net_{(k+1)t}}{\lambda q_{kjt}} = \eta \phi_{kt} \frac{\lambda net_{(k+1)t}}{\lambda q_{kjt}}, \quad (5)$$

$$\Delta Q_{kjt} = \eta \phi_{kt} \frac{\lambda}{\lambda q_{kjt}} \left(\sum_{t=1}^{s_k} O_{kt} Q_{kht} \right) = \eta \phi_{kt} Q_{kj}, \quad (6)$$

$$\Delta Q_{kjt} = -\eta \frac{\lambda X}{\lambda Q_{kjt}} = \eta \phi_{kt} O_{kj}. \quad (7)$$

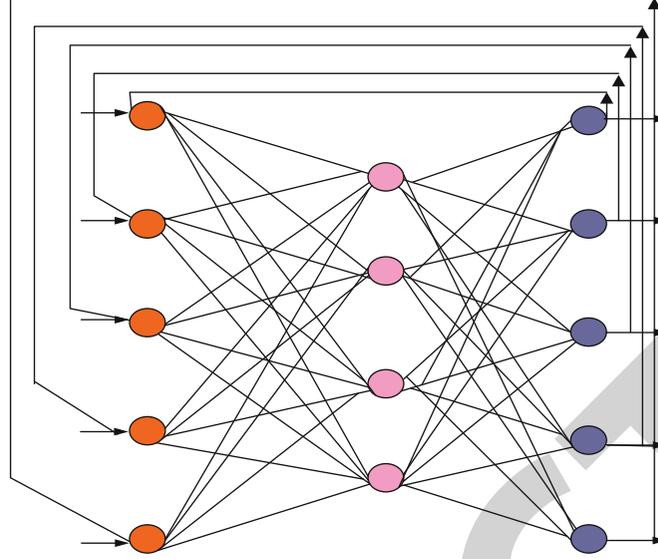


FIGURE 5: Output layer and input layer connected cyclic network structure.

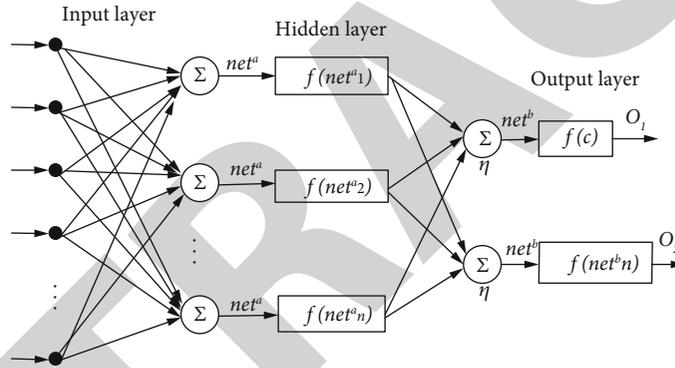


FIGURE 6: BP neural network structure.

At this time,

$$\begin{aligned} \phi_{kt} &= -\frac{\lambda X}{\lambda \text{net}_{(k+1)t}} = -\frac{\lambda X}{\lambda O_{(k+1)t}} \cdot \frac{\lambda O_{(k+1)t}}{\lambda \text{net}_{(k+1)t}} \\ &= -\frac{\lambda X}{\lambda O_{(k+1)t}} f'(\text{net}_{(k+1)t}). \end{aligned} \quad (8)$$

At the same time, according to the function,

$$f'(m) = \frac{x^{-(m-\omega)}}{[1 + x^{-(m-\omega)}]^2} = f(m)[1 - f(m)], \quad (9)$$

$$f'(\text{net}_{(k+1)t}) = f(\text{net}_{(k+1)t})(1 - f) = O_{(k+1)t}(1 - O_{(k+1)t}). \quad (10)$$

Assuming that the output node of the BP neural network

is $O_{(k+1)t}$ at this time, then,

$$\frac{\lambda X}{\lambda O_{(k+1)t}} = n_t - u_t; \quad \left[X = \frac{1}{2} \sum_j (u_j - n_j)^2 \right]. \quad (11)$$

$$\begin{aligned} \phi_{kt} &= -\frac{\lambda X}{\lambda \text{net}_{(k+1)t}} = -\frac{\lambda X}{\lambda O_{(k+1)t}} \cdot \frac{\lambda O_{(k+1)t}}{\lambda \text{net}_{(k+1)t}} \\ &= (u_t - n_t) O_{(k+1)t} (1 - O_{(k+1)t}), \end{aligned} \quad (12)$$

$$\phi_{kt} = (u_t - n_t) n_t (1 - n_t) = (u_t - O_{it}) O_{it} (1 - O_{it}). \quad (13)$$

If $O_{(k+1)t}$ is the hidden layer node of the BP neural network at this time, then,

$$\frac{\lambda X}{\lambda \text{net}_{(k+1)t}} = \sum_{h=1}^{S_{k+1}} \frac{\lambda X}{\lambda \text{net}_{(k+2)h}} \cdot \frac{\lambda \text{net}_{(k+2)h}}{\lambda O_{(k+1)t}} = -\sum_{h=1}^{S_{k+1}} \phi_{(k+1)h} q_{(k+1)th}, \quad (14)$$

$$\text{net}_{kj} = \sum_{h=1}^{s_{k-1}} \phi_{(k-1)t} q_{(k-1)th}. \quad (15)$$

When AA is a hidden layer node of the BP neural network, there will be errors between the predicted output and the actual output. And the total error has a certain connection with the output layer, where h in formula (16) is a certain neuron. At this time, the output of the hidden layer of the BP neural network will have a certain impact on the input of each node in the next layer [17].

$$\phi_{kt} = O_{(k+1)t} \left(1 + O_{(k+1)t}\right) \sum_{h=1}^{s_{k+1}} \phi_{(k+1)h} q_{(k+1)th}, \quad (16)$$

$$\phi_{kt} = \begin{cases} (u_t - n_t) n_t (1 - n_t), \\ O_{(k+1)t} \left(1 + O_{(k+1)t}\right) \left(\sum_{h=1}^{s_{k+1}} \phi_{(k+1)h} q_{(k+1)th} \right), \end{cases} \quad (17)$$

$$\Delta Q_{kjt} = \eta (u_t - n_t) n_t (1 - n_t) O_{kj}, \quad (18)$$

$$\Delta Q_{kjt} = \eta O_{(k+1)t} \left(1 + O_{(k+1)t}\right) \left(\sum_{h=1}^{s_{k+1}} \phi_{(k+1)h} q_{(k+1)th} \right) O_{kj}, \quad (19)$$

$$Q_{kjt}(v+1) = Q_{kjt}(v) + \Delta Q_{kjt} = Q_{kjt} + \eta \phi_{kt} O_{kj}, \quad (20)$$

$$\Delta \omega_{kt} = -\eta \frac{\lambda X}{\lambda \omega_{kt}} \eta (u_t - n_t) n_t (1 - n_t), \quad (21)$$

$$\Delta \omega_{kt} = -\eta \frac{\lambda X}{\lambda \omega_{kt}} = \eta O_{(k+1)t} \left(1 + O_{(k+1)t}\right) \left(\sum_{h=1}^{s_{k+1}} \phi_{(k+1)h} q_{(k+1)th} \right). \quad (22)$$

The error will be corrected until it reaches a minimum error.

2.3. Edge Computing Drives the Deep Learning System Model in Real-Time Artificial Intelligence. Deep learning has always been one of the mainstream technologies in the field of artificial intelligence. Deep learning relies on a lot of calculations, and in this article, we need to talk about the use of artificial intelligence for automated decision-making laws and regulations. It has certain restrictions and algorithm discrimination, such as race, appearance, and judges the professionalism of the work based on clothing [18]. The related theories of deep learning have universal approximation theorem, which states that a single-layer feedforward network with infinite neurons can approximate any continuous function on a compact real subset. This is the existence of algorithmic black boxes, which may attribute a person's education level to the region. It does not have the flexibility of a human brain. In order to solve this kind of algorithm discrimination, this article will propose to use edge computing to improve the artificial intelligence algorithm problem, that is, use the algorithm to suppress the algorithm and adjust the algorithm. Figure 7 shows the inference optimization based on the deep learning model based on the collaboration of the edge and the terminal:

It can be seen that this design has an offline training phase to train branch networks that can meet the task requirements. And it trains regression models for different training networks to analyze the performance of edge servers and terminal collaboration tools. According to different deep learning model network layers, the delay estimation model of the regression model is constructed [19]. Different deep learning model network layers include convolutional layer and pooling layer. In the online optimization stage, the best exit point and time delay estimation model split point were sought. Artificial intelligence can measure the link network bandwidth of mobile terminals and edge service devices in real time [20–22]. The purpose is to estimate the delay in real time, find the cut point that meets the delay requirement, and obtain the point with the best accuracy for output. In the collaborative inference stage, the edge server and mobile terminal perform collaborative inference on the artificial intelligence deep learning network based on the best segmentation point output in the optimization stage [23–25]. Finally, it can be concluded that this system model can meet the requirements under different calculation delay requirements, and realize high-precision model reasoning. That is, when this model is applied to legal regulations, it can cooperate with edge computing and artificial intelligence algorithms to provide high-precision automated decision-making [26–28]. The model can be applied to the field of artificial intelligence, law, education, drones, transportation, urban information planning systems, etc.

3. Artificial Intelligence-Assisted Automated Decision-Making Experiment Based on the Theory of Legal Computing

3.1. Clustering Scheme Based on Artificial Intelligence Bayesian Decision Theory. Bayesian decision theory is often used for automated decision-making in artificial intelligence. According to different decision rules, it can be divided into two kinds, one is Bayesian decision theory with minimum error rate, and the other is Bayesian decision theory with minimum risk. The Bayesian decision with the smallest error rate can find the classification result with the highest correct rate. But in actual problems, the cost of misclassification of different categories may be different. For example, the cost of classifying poisonous mushrooms as nontoxic mushrooms is far greater than the cost of classifying nontoxic mushrooms as poisonous mushrooms. Therefore, according to the actual situation, the risk of classification error is artificially introduced, which makes Bayesian decision-making more scientific.

When the value of the loss function is between 0 and 1, the Bayesian decision theory of minimum error rate is in the minimum risk state. The Bayesian decision theory is used to study clustering problems, and the risk assessment function of clustering schemes is constructed. At this time, the similarity measurement is performed on the clustered data set, the similarity matrix is obtained according to the similar information, and the similarity is judged by the threshold.

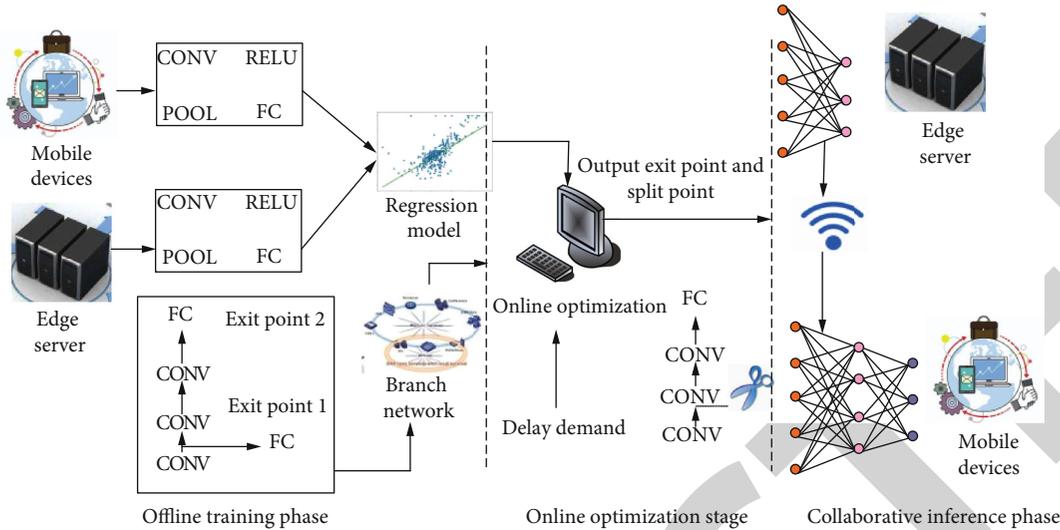


FIGURE 7: Artificial intelligence deep learning model operation inference optimization based on edge computing and terminal collaboration.

The Bayesian algorithm to assist decision-making can classify data according to its characteristics and present the data conclusions in the form of probability to a certain extent. In legal cases, under the state of legal regulations such as lawyers' decision-making, naive Bayes judges data based on legal cases and analyzes the risks and winning rate of legal cases of unknown cases. This process can be realized by learning and training data samples and generalizing the corresponding probability model. It seeks conclusions in the model and predicts results and probabilities. In legal relations, when the winning rate is higher than 50%, it is easier to obtain support for the appeal in a specific legal case under ideal conditions. This article will take traffic accident disputes as an example, participating roles in traffic accident disputes are the owner or manager of the road traffic accident vehicle. Other personnel that the traffic management department of the public security organ deems necessary to participate and use artificial intelligence Bayesian decision-making theory to assist in litigation decision-making on unknown cases in certain scenarios. At this time, due to the complexity of the legal relationship, artificial intelligence has algorithm discrimination, and there are a large number of components. This article will use the edge computing in 2.3 for auxiliary operations. This experimental data set comes from 266 legal case history in a court. Combining the same record lines according to the characteristics, this article also completes the possible situations in the regulations, forming a 248-line legal relationship data set. Using artificial intelligence decision tree for classification processing, the relationship between each feature attribute and regulation in the data set is shown in Table 1.

Experiments on legal decision-making are based on this model. According to the classification of the decision tree, the corresponding legal relationship is a traffic accident dispute, and the data point that is the closest to the original legal relationship model is the point of high similarity.

This experiment is based on 266 data records in the data set sample trained and learned in traffic accident cases, com-

bin with the naive Bayes algorithm in artificial intelligence, to predict the probability of winning a legal case. The probability of winning a legal case by combining the characteristic elements corresponding to the data points that conform to the legal relationship and other similar data points was predicted. The characteristic attributes and judgment results of the obtained data are shown in Tables 2 and 3:

According to the observation of the table, if the lawyer moves the traffic accident case closer to the characteristic data combination A2, the probability of winning the legal case can be improved. Under the naive Bayesian decision-making theory based on artificial intelligence, the probability of winning a case will increase by 4.2%.

3.2. Experimental Analysis of Data Clustering Combining Edge Computing and Bayesian Algorithm. Using Bayesian decision theory to construct a clustering plan for risk assessment, the better the clustering effect obtained at this time, the smaller the risk value. Fusion edge computing adjusts the Bayesian algorithm in artificial intelligence and observes whether it has better results. At this time, part of the data in the case is extracted as the data set Data1 and the data set Data2. Figure 8 shows the clustering effect of Data1's original data set and Bayesian algorithm:

Figure 9 shows the clustering effect of Data2's original data set and Bayesian algorithm:

Then, this paper compares the clustering results between the Bayesian algorithm of artificial intelligence and the Bayesian algorithm of edge computing fusion artificial intelligence proposed in this article. The test data is 6 sets of data in traffic accident cases. The performance is tested, and Figure 10 is obtained:

It can be seen that the clustering effect of the artificial intelligence Bayes algorithm improved by edge computing is increased by about 7.2%. In the application of regulations and cases, it is undoubtedly able to better classify and recognize data. It has higher accuracy, reduces algorithm

TABLE 1: Data characteristic attributes of the experimental model library and the number of corresponding model record rows.

| Characteristic attribute | Attribute value | Legal model 0 | Legal model 1 | Legal model 2 | Legal model 3 | Legal model 4 | Total |
|--------------------------|-----------------|---------------|---------------|---------------|---------------|---------------|-------|
| c1 | 0 | 0 | 0 | 0 | 0 | 72 | 72 |
| | 1 | 12 | 2 | 8 | 3 | 36 | 62 |
| c2 | 0 | 24 | 4 | 8 | 2 | 96 | 134 |
| | 1 | 18 | 12 | 2 | 0 | 62 | 95 |
| ... | | | | | | | |
| c6 | 0 | 18 | 0 | 6 | 2 | 78 | 104 |
| | 1 | 16 | 0 | 8 | 0 | 78 | 102 |
| Total | | 36 | 10 | 5 | 2 | 195 | 248 |

TABLE 2: The characteristic attributes of the sample data of traffic accident cases and the number of record rows of the trial results.

| Characteristic attribute | Attribute value | Value = 0 | Value = 1 | Total |
|--------------------------|-----------------|-----------|-----------|-------|
| c1 | 0 | 104 | 24 | 128 |
| | 1 | 72 | 64 | 136 |
| c2 | 0 | 98 | 32 | 130 |
| | 1 | 78 | 52 | 130 |
| ... | | | | |
| c6 | 0 | 99 | 46 | 145 |
| | 1 | 78 | 44 | 122 |
| Total | | 182 | 84 | 266 |

TABLE 3: Prediction of probability of success in traffic accident cases based on experimental data points and similar data points.

| Feature combination requirements | Priori probability | Full probability | Posterior probability |
|----------------------------------|--------------------|------------------|-----------------------|
| A0 | 0.00927 | 0.01302 | 0.7392 |
| A1 | 0.00843 | 0.01329 | 0.6298 |
| A2 | 0.00931 | 0.01277 | 0.7433 |
| A3 | 0.00612 | 0.01101 | 0.5588 |
| A4 | 0.00211 | 0.00748 | 0.2883 |
| A5 | 0.00428 | 0.00861 | 0.4296 |

discrimination caused by artificial intelligence, and uses algorithms to correct algorithms. Algorithmic discrimination is in the process of people using artificial intelligence, through a series of calculations within the algorithm to harm the basic rights of citizens. A rule that violates social public ethics or an algorithm set by the maker itself is an unfair rule.

3.3. Verification of Decision Accuracy. Next, this article will test the accuracy of the decision-making and use a certain coefficient to test the consistency of the experimental result data, which is called the measurement parameter. The law itself is relatively abstract, vague, and subjective, and the conclusion of a decision does not necessarily have to be right or wrong. Therefore, human thoughts will be used as the measurement carrier here to demonstrate the accuracy of

the experimental results. It tests the accuracy of decision-making results from a side perspective. This article will give the degree of dispersion of decision-making experiments and questionnaire surveys.

First, the data combination of A1 to A5 is used to predict the winning rate statistics of the experimental samples using the naive Bayes algorithm. The 6-line feature record is used as the experimental sample, and then, the naive Bayes algorithm improved by edge computing is used to predict the winning rate of the experimental sample. By recording the difference between the results of the two experiments, the difference between the two is shown in Figure 11.

It can be seen that the naive Bayes algorithm improved by edge computing can indeed improve the winning rate. The recognition of 64 lawyers and 58 legal researchers on the results of this experiment was reinvestigated. This time, one lawyer and 2 legal researchers have a negative attitude towards this experiment. All three people hold negative attitudes that the legal relationship is complicated and that edge computing cannot make a good improvement to the algorithm discrimination of artificial intelligence. The results are shown in Figure 12.

It can be seen that this experiment has a certain feasibility. Although it is inevitable that there will be crossover issues of legal relations, it can also improve the regulatory effects of laws and regulations to a certain extent and reduce algorithmic discrimination caused by artificial intelligence. And its clustering effect of the artificial intelligence Bayes algorithm improved by edge computing is increased by about 7.2%.

4. Discussion

This paper proposes a Bayesian algorithm that uses edge algorithms to merge into artificial intelligence. It uses algorithms to adjust algorithms to reduce artificial intelligence algorithm discrimination. The experimental sample used in this article is a history of 266 legal cases in a court. Combining the same record lines according to the characteristics, this article also completes the possible situations in the regulations to form a 248-line legal relationship data set and uses an artificial intelligence decision tree for classification. The feasibility of the algorithm fusion proposed in the experiment is verified through the case winning rate, the Bayesian algorithm purity of Bayesian algorithm and edge

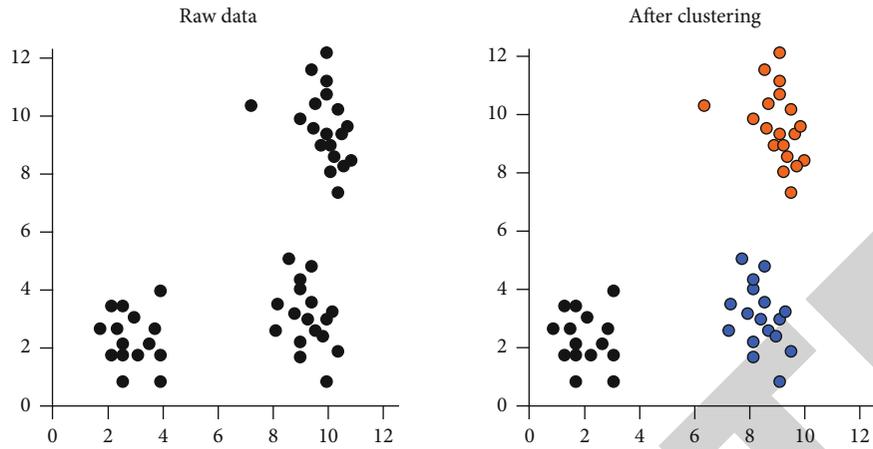


FIGURE 8: Data1 before and after clustering.

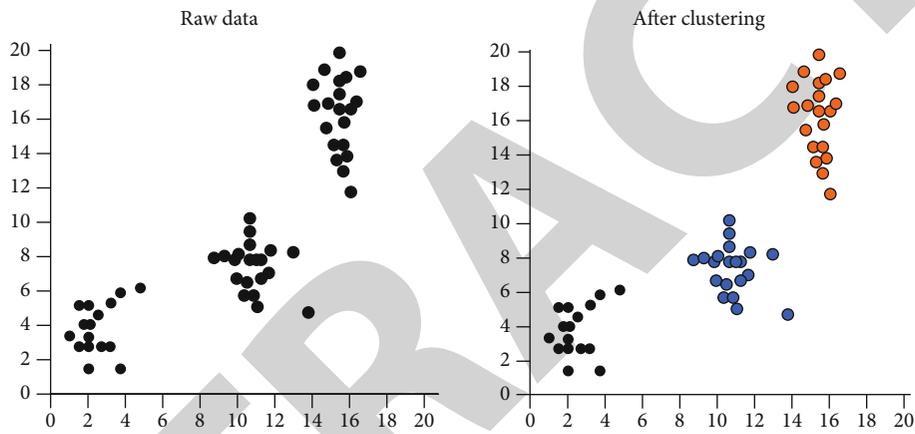


FIGURE 9: Data2 before and after clustering.

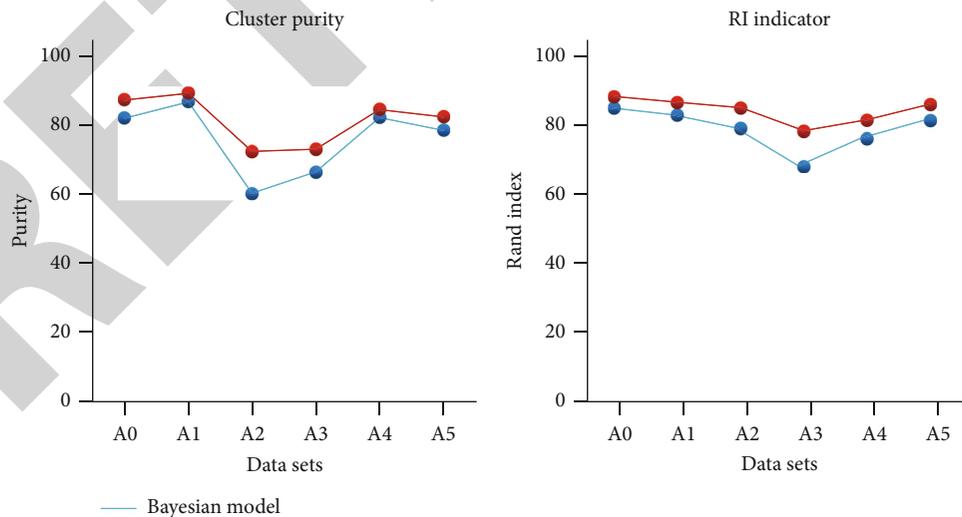


FIGURE 10: Comparison of Bayesian algorithm purity and RI index of Bayesian algorithm and edge computing fusion artificial intelligence.

computing fusion artificial intelligence, and the RI index and data clustering before and after comparison. Bayesian decision theory is often used in automated decision-making by artificial intelligence. Different decision-making methods

can be selected according to different decision rules. This article is to study the Bayesian decision theory of minimum risk. It compares the clustering results between the Bayesian algorithm of artificial intelligence and the Bayesian

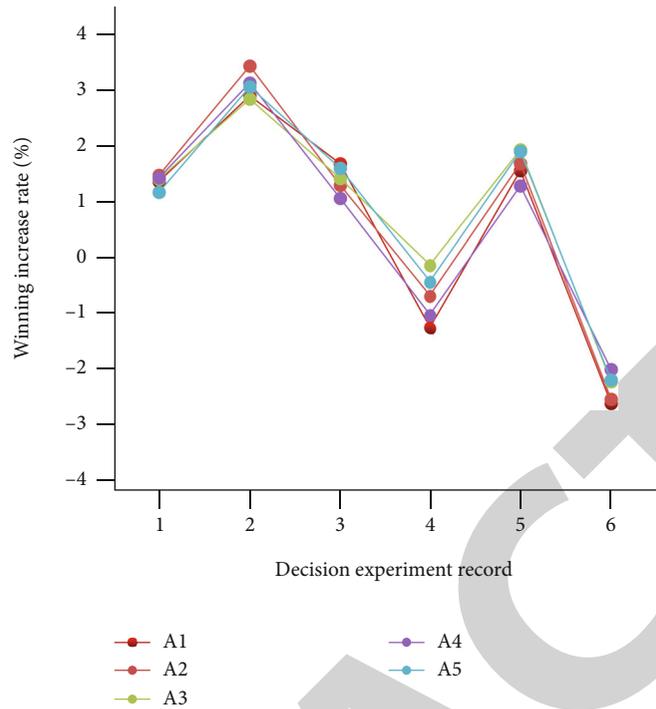


FIGURE 11: Dispersion of decision-making experiment results.

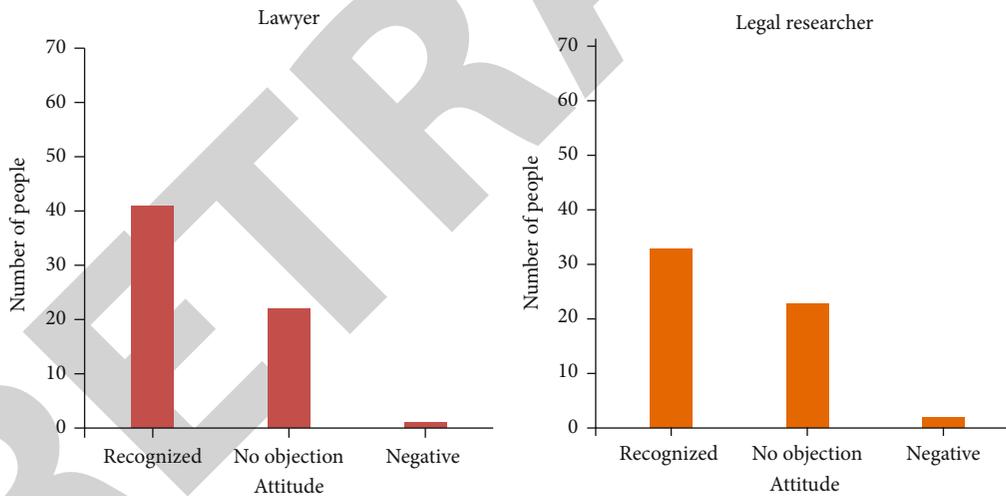


FIGURE 12: Survey of legal workers' attitudes towards the results of this experiment.

algorithm of edge computing and artificial intelligence proposed in this paper. The Bayesian algorithm that uses edge algorithms to integrate artificial intelligence can improve the regulatory effect of laws and regulations to a certain extent, reduce algorithm discrimination caused by artificial intelligence, and have stronger clustering capabilities. The test data is 6 sets of data in traffic accident cases to test its performance. Finally, this article also sent out questionnaires to 64 lawyers and 58 legal researchers through a questionnaire survey to investigate their attitudes towards the experiment. Experiments show that the artificial intelligence edge

computing plus Bayesian algorithm proposed in this article is indeed feasible, and it has a certain ability to regulate algorithm discrimination caused by artificial intelligence in legal regulations.

5. Conclusion

When experimenting with the Bayesian algorithm that uses edge algorithms to be integrated into artificial intelligence, this article uses data from a traffic accident case obtained from a court to design the experiment. This article records

data from 266 legal cases. According to the classification of data characteristics, this article uses artificial intelligence decision tree to obtain the characteristic attributes of the sample data of traffic accidents and the number of records of the trial results and the winning rate. And this paper divides it into multiple feature data sets, performs cluster analysis, and tests the algorithm purity and RI index under the Bayesian decision theory and the edge algorithm optimization. Finally, this paper tests the dispersion of the results of the decision-making experiment and concludes that the probability of winning a case will increase by 4.2% compared with purely human-handled cases under the naive Bayesian decision-making theory based on artificial intelligence. And this article uses the edge computing improved artificial intelligence Bayesian algorithm to improve the clustering effect by about 7.2%. The Bayesian algorithm that uses edge algorithms to integrate artificial intelligence can improve the regulatory effect of laws and regulations to a certain extent and reduce algorithm discrimination caused by artificial intelligence. Improving laws and regulations can form a society in which democracy and the rule of law, fairness and justice, honesty and friendship, full of vitality, stability and order, and harmony between man and nature can be formed.

Data Availability

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Conflicts of Interest

The author states that this article has no conflict of interest.

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