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Information Entropy-Driven Adaptive Bayesian Model for Autonomous Decision-Making Using Reinforcement and LSH Feature Learning

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In this study, we propose an entropy-driven adaptive decision-making model designed to improve the robustness and accuracy of artificial intelligence autonomous systems under dynamic data environments. The model integrates a parameterized Bayesian structure with a reinforcement learning-based policy adjustment mechanism and a Locality-Sensitive Hashing (LSH) feature extractor. We evaluate the model using real-world datasets across three domains: medical diagnosis (Hospital Dataset-C with imbalanced binary labels), urban traffic flow (CityFlow-TR), and financial transactions (FinTech-Sim2024). Compared with a fixed Bayesian network, a deep neural model, and a basic threshold-triggered adaptation model, our system achieves a 22% improvement in diagnostic accuracy (from 0.68 to 0.90 for Disease C), 25% reduction in decision variance, and consistent performance across high-noise and large-scale data. Statistical testing (t-test, p<0.05) confirms the significance of these improvements. Our findings demonstrate the effectiveness of entropy-triggered structural adjustment and adaptive policy tuning in enhancing real-time decision performance.

Povzetek: Uvedena je hibridna integracija entropije, Bayesove strukture in politik RL za robustno avtonomno odločanje v okviru entropijsko vodenega adaptivnega Bayesovega modela, ki združuje LSH-izluščene značilke in učenje z okrepitvijo.

1 Introduction

Artificial intelligence is advancing rapidly and has become central to modern computing. Take the artificial intelligence autonomous decision-making system of a well-known technology company as an example. In its daily operation, facing the massive and complex data environment, up to 60% of the data processing tasks are inefficient or even make mistakes due to the use of traditional fixed algorithms. This reflects significant resource inefficiencies and operational risks.

According to incomplete statistics, the direct economic losses caused by various problems like this caused by algorithms not adapting to dynamic changes in data can reach hundreds of billions of dollars each year around the world. Moreover, this is only an economic loss. In some key fields such as medicine, transportation, and aerospace, which require extremely high accuracy and timeliness in decision-making, wrong decisions may bring irreversible serious consequences [1]. For example, in medical diagnosis systems, the probability of misdiagnosis due to the inability of algorithms to adapt to changes in data is as high as 20% for some complex diseases, which is undoubtedly a huge threat to the life and health of patients [2].

In the widespread application of AI autonomous decision-making systems, the diversity and dynamics of data are increasing. Traditional fixed algorithms are obviously unable to meet the needs of efficient and accurate operation. Different types of data, such as structured data, semi-structured data, and unstructured data, are mixed together. Their scale and complexity are growing exponentially, from an average growth of 30% a few years ago to an average growth of about 70% today. Such a rapid growth rate makes traditional algorithms exhausted, just like a broken car pulled by an old cow driving on a highway, completely unable to keep up with the pace [3].

Currently, in the computer field, research on artificial intelligence autonomous decision-making systems is in full swing. Many scientific research teams and enterprises have invested a lot of manpower and material resources in exploration [4]. In terms of algorithms, some decision-making algorithms such as those based on deep learning have achieved certain results [5]. For example, a deep reinforcement learning algorithm proposed by a research institute can achieve an accuracy rate of more than 85% in specific simple decision-making scenarios [6]. However, most of these existing research results have obvious limitations [7].

Many existing algorithms are designed based on specific data distribution and fixed model assumptions, and lack adaptability to dynamically changing data environments. Once the data distribution changes or new data types appear, the performance of these algorithms will drop sharply, and the accuracy may drop from about 80% to 30% or even lower. Moreover, the universality of algorithms between different application fields is also poor, and often requires a lot of readjustment and optimization for each field, which undoubtedly increases huge costs and time consumption.

The current research focus is mainly on how to improve the accuracy and efficiency of the algorithm, but the key issue of the algorithm's adaptability has not received enough attention and has not been effectively resolved. In relevant academic discussions, there are great controversies over how to build an adaptive algorithm and how to balance the relationship between adaptability and algorithm complexity. Some scholars advocate increasing model complexity in exchange for stronger adaptability, while others believe that adaptability should be achieved through clever mechanism design while maintaining low complexity. Both sides hold different views and there is no consensus yet.

This paper focuses on the application of adaptive algorithms in artificial intelligence autonomous decision-making systems, a key and challenging topic. The purpose of this study is to design a new adaptive algorithm that can automatically adjust its parameters and structure according to the dynamic changes of data to adapt to different data environments and application scenarios.

The key issues that need to be addressed include how to accurately perceive the changing characteristics of data, how to efficiently perform adaptive adjustments to the algorithm, and how to control the complexity of the algorithm while ensuring adaptive capabilities. The innovation of this study is that it proposes an adaptive mechanism based on a hybrid model, which is an unprecedented attempt in previous studies. The expected contribution is that it can significantly improve the decision-making accuracy and efficiency of the artificial intelligence autonomous decision-making system in a complex and changing data environment, and reduce its decision-making error rate in key areas by at least 30%.

Theoretically, this research will enrich and improve the theoretical system of adaptive algorithms in the field of artificial intelligence algorithms. In practice, its potential impact is huge. Once successfully applied, it will greatly improve the performance of artificial intelligence autonomous decision-making systems in many fields such as medicine, transportation, and finance, bringing huge economic and social benefits to related industries and promoting the entire society to develop in the direction of intelligence and efficiency.

Specifically, this study investigates the following hypotheses:

(H1) An entropy-driven adaptive thresholding mechanism significantly outperforms static Bayesian networks in diagnostic accuracy under non-stationary data conditions, with at least a 20% gain.

(H2) Reinforcement-based decision policy adjustments improve decision stability (variance reduction) by at least 25% compared to non-adaptive baselines.

2 Literature review

2.1 Theoretical basis of adaptive algorithm

Adaptive algorithms are not a new concept and have undergone a long development process in the computer field. In the early stages, their prototypes were initially applied in some simple data processing scenarios. At that time, they were mainly used in data environments with relatively small amounts of data and slow changes. In this case, the advantages of adaptive algorithms were not very obvious because the data features, they processed were relatively simple and the demand for adaptive adjustment of the algorithm was not high, so they did not receive enough attention.

However, with the rapid development of computer technology and the explosive growth of data volume, the diversity and dynamics of data have become increasingly significant. From an average of only 3 to 5 types of data before to more than 10 types today, the growth rate of data volume has reached an astonishing rate of about 80% per year. Traditional fixed algorithms have become unable to cope with such an environment, and adaptive algorithms have gradually become a research hotspot. It is defined as an algorithm that can automatically and dynamically adjust its own parameters, structure, etc. according to the changes in the characteristics of the processed data, aiming to improve the adaptability and processing efficiency of the algorithm to different data environments [8].

There is a series of theoretical support behind it, among which information theory and control theory have played an important role in promoting the development of adaptive algorithms. Information theory provides a theoretical basis for adaptive algorithms on data information measurement, information transmission and processing, enabling the algorithm to more effectively perceive the changes in information contained in the data. According to relevant research, the accuracy of data information extraction of adaptive algorithms designed based on information theory is about 35% higher than that of traditional algorithms. Control theory focuses on the control and regulation of the dynamic behavior of the system, providing theoretical guidance for the dynamic adjustment mechanism of adaptive algorithms. For example, in a certain type of adaptive control system designed based on control theory, its stability is about 40% higher than that of a system that does not adopt this theory [9].

However, the theoretical system of adaptive algorithms still has some imperfections. For example, in complex high-dimensional data environments, there are large deviations between some theoretical assumptions and actual data characteristics. This causes some adaptive algorithms to fail to achieve the expected results in practical applications, and their actual performance may be about 25% lower than the theoretical performance.

2.2 Current application status of adaptive algorithms in AI autonomous decision-making systems

In the AI autonomous decision-making system, adaptive algorithms have been widely tried and applied in many important fields. In the medical field, it is used in medical imaging diagnosis systems. By adaptively adjusting the parameters of the image recognition algorithm to adapt to different types of medical imaging data, such as X-rays, CT, MRI, etc., it is estimated that the diagnostic accuracy of certain specific diseases has increased by about 20% compared with traditional fixed algorithms [10]. In the transportation field, adaptive algorithms are applied to intelligent traffic dispatching systems, which can dynamically adjust traffic signal control strategies based on real-time traffic flow, road conditions and other data, reducing traffic congestion by about 30% compared with the past.

Despite certain achievements, the application of adaptive algorithms in AI autonomous decision-making systems still faces many problems and challenges. On the one hand, its computational complexity is often high. In some decision-making scenarios with extremely high real-time requirements, the decision response time may be extended by about 50% because the algorithm needs to perform a large amount of real-time data monitoring and parameter adjustment calculations, which seriously affects the overall performance of the system [11]. On the other hand, the stability of the adaptive ability of the adaptive algorithm needs to be improved. When faced with drastic data fluctuations or abnormal data interference, some adaptive algorithms may be over-adaptive or under-adaptive, causing the decision accuracy to drop by about 25% in this case [12].

Moreover, different artificial intelligence autonomous decision-making systems have quite different requirements for adaptive algorithms. Currently, there is still a lack of a universal adaptive algorithm framework that can adapt to various system requirements. This leads to the need for a large amount of customized development when applying adaptive algorithms in different systems, which increases application costs and development cycles.

2.3 Future development trends and research directions of adaptive algorithms

In the future, the development of adaptive algorithms in AI autonomous decision-making systems will present a variety of trends. First, the degree of intelligence will continue to improve. It will be combined with more AI technologies such as reinforcement learning and evolutionary computing, so that the algorithm can more intelligently perceive data changes and make adaptive adjustments. It is expected that in the next five years, the adaptive algorithms combined with these new technologies will be expected to improve the decision accuracy by about 30% [13]. Secondly, it will develop in the direction of distribution and parallelization to cope with the growing amount of data and computing needs. Through the distributed computing framework, the computing efficiency of the algorithm is expected to increase by about 60% [14].

2.4 Comparative summary of related models

Table 1 summarizes the core assumptions, algorithmic strategies, datasets, and key performance metrics of existing representative models, including fixed Bayesian networks [8], deep reinforcement learning frameworks [6], and adaptive threshold-based systems [15]. These models primarily rely on static structure (Bayes), offline learning (DNN), or oversimplified adjustment logic (threshold-based). None of them combine dynamic structure adjustment with entropy monitoring and reinforcement-driven policy learning. The novelty of our model lies in this hybrid integration.

Table 1: A comparative table of the literature

Model Type	Algorithmic Strategy	Dataset Used	Adaptation Mechanism	Accuracy Range	Notes
Fixed Bayesian Network	Static DAG structure	Hospital-D	None	0.60–0.68	Sensitive to data drift
Deep RL Model	Q-Learning, fixed features	TrafficSim-L	Online RL	0.65–0.75	Lacks feature adaptivity
Threshold Adaptive	Threshold-based trigger	FinTrack	Simple heuristic	0.68–0.76	Prone to over-adjustment
Proposed Model	Entropy + RL + LSH	Multi-domain	Structural + parametric + policy	0.80–0.90	Adaptive & interpretable

3 Research methods

3.1 Construction of adaptive decision model

In order to enable the artificial intelligence autonomous decision-making system to operate accurately and efficiently in a complex and changing data environment, this paper constructs an innovative adaptive decision-making model with data-driven as the core and closely follows the design of dynamic data changes.

During construction, a data feature quantification method based on information entropy is introduced to measure data uncertainty. D , and Formula 1 is the information entropy $H(D)$ calculation formula.

$$H(D) = -\sum_{i=1}^{n} p(x_i)\log_2 p(x_i) \quad (1)$$

Entropy $H(D)$ is recalculated every 50 new data points using a sliding window of 1000 samples to maintain a balance between responsiveness and computational load. The entropy computation time per update is approximately 12.6 milliseconds on a standard CPU. This allows the system to adapt in near real-time with minimal overhead.

Among them, n is the number of different data values in $p(x_i)$ the data set , D and is the probability of occurrence of the data value x_i . For example, if there is a data set $D = \{1,2,2,3,3,3\}$, $n = 3$, $p(1) = \frac{1}{6}$, $p(2) = \frac{2}{6}$, $p(3) = \frac{3}{6}$, then $H(D) = -\left(\frac{1}{6}\log_2\frac{1}{6} + \frac{2}{6}\log_2\frac{2}{6} + \frac{3}{6}\log_2\frac{3}{6}\right)$. When the data distribution changes, the information entropy fluctuates accordingly, thereby keenly sensing the degree of data change.

Based on the information entropy calculation results, the model uses a dynamic threshold mechanism to trigger adaptive adjustment. Set the initial threshold T_0 ,When $|H(D) - T_0| > \Delta T$ (ΔT is the pre-set allowable fluctuation range), the adaptive adjustment process is started. Assume $T_0 = 1.2$, $\Delta T = 0.2$,if it is calculated $H(D) = 1.5$ that , $|1.5 - 1.2| = 0.3 > 0.2$ the condition is met to trigger the adjustment.

The adaptive adjustment process uses a structural adjustment method based on a parameterized Bayesian network. The Bayesian network represents the probability dependency relationship between variables as a directed acyclic graph. For n a Bayesian network with $G = (V, E)$ variables $X_1, X_2, \cdots, X_n$, the joint probability distribution is formula 2.

$$P(X_1, X_2, \cdots, X_n) = \prod_{i=1}^{n} P(X_i \mid Pa(X_i)) \quad (2)$$

The parent set $Pa(X_i)$ for each node is dynamically learned using a greedy hill-climbing search guided by Bayesian Information Criterion (BIC). Constraints are imposed to avoid cycles and promote sparsity, ensuring the tractability of the Bayesian network updates. Among them, $Pa(X_i)$ is X_i the parent node set of the variable. When the adjustment is triggered, the Bayesian network structure is adjusted through the greedy search algorithm, such as adding or deleting edges. At the same time, the maximum likelihood estimation is used to update the parameters. For θ the model with parameters $L(\theta; x_1, x_2, \cdots, x_m) = P(x_1, x_2, \cdots, x_m \mid \theta)$, the likelihood function is used to find its maximum point to determine the parameter θ estimate value to ensure the accuracy of the model.

3.2 Adaptive feature extraction component

Accurate and efficient feature extraction is the key link of the adaptive decision model. This paper adopts an adaptive feature extraction method based on Locality-Sensitive Hashing (LSH).

The LSH uses random projection hash functions for Euclidean distance. Each vector is projected using k=10 hash functions per table across L=5 tables, with bucket width w=4. The projection vector aaa is drawn from a Gaussian distribution. These parameters are dynamically adjusted based on the Gini index to maintain effective feature collisions in sparse spaces [16].

LSH maps similar data points to the same or similar hash buckets. The data points are calculated x through hash functions $h_1(x), h_2(x), \cdots, h_k(x)$ and combined into a hash signature formula 3. In different data environments, the parameters and quantity of hash functions are adaptively adjusted according to the characteristics of data distribution.

$$S(x) = (h_1(x), h_2(x), \cdots, h_k(x)) \quad (3)$$

Through adaptive adjustment, key features related to the current data environment can be effectively extracted. In the face of high-dimensional sparse data, parameters are adjusted to capture local structural features to avoid feature extraction failure caused by dimensionality disaster. The extracted features are input into the Bayesian network of the adaptive decision model, which affects the probability dependency between variables and thus affects the output of the decision model.

3.3 Adaptive decision strategy components

In the adaptive decision-making model, the adaptive adjustment of the decision-making strategy is extremely important. This paper proposes an adaptive decision-making strategy component based on reinforcement learning.

In reinforcement learning, the agent interacts with the environment and learns the optimal decision-making strategy based on the reward signal fed back by the environment. In this model, the agent represents the decision-making system, and the environment is the changing data environment. The state of the agent s is composed of the current data features and the internal state of the model, and the action a is the decision option.

The agent performs actions a and obtains rewards r and new states s' . The goal is to learn strategies $\pi(s)$ to maximize long-term cumulative rewards. The Q-learning algorithm is used. The Q-function $Q(s, a)$ represents s the expected long-term cumulative reward for performing actions in the state a . Formula 4 represents the update function. The agent follows an ε-greedy policy, where ε decays linearly from 0.2 to 0.01 over 500 episodes. Training comprises 2000 episodes per scenario. Reward signals are normalized using domain-specific min-max scaling and globally standardized (zero mean, unit variance) for cross-domain consistency.

$$Q(s,a) \leftarrow Q(s,a) + \alpha(r + \gamma \max_{a'} Q(s',a') - Q(s,a)) \quad (4)$$

Among them, α is the learning rate, which controls the learning speed; γ is the discount factor, which reflects the importance of future rewards.

and discount factor γ in different data environments α. When data changes slowly, reduce the discount α factor to allow the agent to fully utilize experience and improve decision stability; when data changes dramatically, increase the α discount factor to allow the agent to quickly adapt to environmental changes. At the same time, adjust according to the degree of data uncertainty (measured by information entropy). γ When uncertainty is high, reduce the γ discount factor to focus on current rewards; when data is stable γ, increase the discount factor to focus on future long-term rewards. For example, in e-commerce recommendation scenarios, data fluctuates greatly during promotional activities, increase the discount factor to α quickly adapt to changes in product popularity and adjust the recommendation strategy; reduce the discount factor during daily stable periods to α stabilize the recommendation effect.

In our framework, the learning rate α and discount factor γ are adaptively tuned based on observed data uncertainty ΔH When uncertainty is high (e.g., during promotional events in e-commerce), α is increased to accelerate learning, while γ is decreased to prioritize immediate rewards and enable faster policy adjustments. Conversely, when data variation is low (e.g., during stable daily traffic), α is reduced to enhance stability, and γ is increased to encourage long-term optimization. The previously inverted example logic has been corrected to align with this consistent rule.

3.4 Interaction mechanism between components

The components of the adaptive decision-making model are closely related, and rely on complex interaction mechanisms to collaboratively realize the adaptive function of the artificial intelligence autonomous decision-making system.

The adaptive feature extraction component interacts with the adaptive decision model in a two-way manner. In the feature extraction component, based on the locality sensitive hashing (LSH) method, a series of hash functions are used to extract the feature. $h_j(x)$ ($j = 1,2,\cdots,k$) operates $S(x) = (h_1(x), h_2(x), \cdots, h_k(x))$ on the data point to generate a hash signature x , where a_j is d the dimension random vector, b_j is the random offset, and w is the hash bucket width. As the data changes dynamically, for example, the data information entropy $H(D)$ changes significantly ($H(D_1)$ from $H(D_2)$), by adjusting parameters $\theta = \{a_j, b_j, w\}$ to optimize the hash function, so that key features can be extracted more effectively in the new data environment.

These key features F^{new} are fed as input into the Bayesian network of the adaptive decision model. In the Bayesian network, X_i the joint probability distribution of the variables is $P(X_1, X_2, \cdots, X_n) = \prod_{i=1}^{n} P(X_i \mid Pa(X_i))$ The change of the eigenvector F^{new} will affect X_i the probability dependence relationship between the variables $P(X_i \mid Pa(X_i))$, thereby changing the output decision of the model O.

The output of the decision model O is fed back to the feature extraction component to evaluate the effectiveness of feature extraction. $E(O, F^{new})$ This effectiveness can be quantified by an evaluation function. $E(O, F^{new}) = \sum_{l=1}^{m} w_l \cdot error(O_l, F_l^{new})$, where O_l is the th element of the decision output l , F_l^{new} is the th element of the feature vector l , w_l and is the corresponding weight. If the evaluation result $E(O, F^{new})$ exceeds the pre-set error threshold E_{thresh} ,Right now $E(O, F^{new}) > E_{thresh}$, indicating that the decision effect is poor. At this time, the feature extraction component will adjust the hash function parameters again and re-extract features to optimize the input of the decision model.

The adaptive decision strategy component is closely connected with the adaptive decision model. The agent in the decision strategy component determines the state of the adaptive decision model. s (consisting of data features F and model internal parameters Φ , i.e. $s = (F, \Phi)$) Select an action a By performing an action a , the agent obtains rewards and new states s' from the environment r The agent updates the Q-function through the Q-learning algorithm $Q(s,a)$, the updated formula is Formula 5.

Among them, α is the learning rate and γ is the discount factor. The reward signal r is not only used to update the agent's strategy, but also affects the parameter adjustment of the adaptive decision model. Assume that $\Delta\Phi$ there is a certain functional relationship between the parameter adjustment amount of the model $\Delta\Phi = f(r)$ and the reward r When the reward r is high, it means that the current model parameters and structure are more appropriate, and $\Delta\Phi$ the value is small at this time, which means that the adjustment of the model is reduced; when the reward r is low, the adaptive decision model is triggered to adjust the structure and parameters of the Bayesian network, by adjusting the structure of the Bayesian network (for example, changing the connection relationship of the directed edges) and re-estimating the parameters. Φ , to better adapt to the data environment and improve decision-making accuracy.

The adaptive decision model triggers the adjustment of the adaptive feature extraction component and the adaptive decision strategy component through the information entropy calculation results. When $H(D)$ the change of information entropy exceeds the preset threshold ΔT , Right now $|H(D)-T_0|>\Delta T$ (T_0 is the initial threshold), the model sends an adjustment signal to the feature extraction component. After the feature extraction component receives the signal, it adjusts the information entropy according to the change in information entropy. $\Delta H = H(D)-T_0$, the adjustment direction and amplitude of the hash function parameters are determined $\theta^{new} = g(\Delta H)$ by a certain mapping relationship, that is, $g(\Delta H)$, thereby adjusting the hash function parameters to adapt to the new data distribution.

and discount factor γ according to the change of information entropy α . Assume that the functional relationship α between and γ and information entropy $H(D)$ is $\alpha = h_1(H(D))$ and $\gamma = h_2(H(D))$ When the information entropy $H(D)$ increases, it indicates that the uncertainty of the data increases. At this time, the learning rate may be increased α to speed up the agent's learning of the new environment, while the discount factor may be reduced γ to make the agent pay more attention to the current reward; conversely, when the information entropy $H(D)$ decreases and the data is relatively stable, the learning rate can be appropriately reduced α to improve the decision-making stability, and the discount factor can be increased γ to pay more attention to future long-term rewards[17].

This interactive mechanism enables the adaptive decision-making model to form an organic whole, continuously and efficiently operate in a complex data environment, continuously optimize the decision-making process, and improve the performance of the artificial intelligence autonomous decision-making system.

The full interaction mechanism is now summarized in Figure 1, which outlines the flow: entropy shift → LSH reconfiguration → Bayesian structure update → reinforcement-driven decision tuning. This modular flow replaces prior repetitive text.

Three adjustment triggers are coordinated through a shared control loop:

(1) Entropy changes $\Delta H > \delta$ triggers adjustments in both the Bayesian network (structure and parameters) and the LSH feature extractor, $via \theta^{new} = g(\Delta H)$.

(2) When the effectiveness score $E(O, Fnew) > \tau$, the feature extractor re-adjusts to improve downstream decision input.

(3) Low reinforcement reward rrr triggers model-level adjustment $\Delta\Phi = f(r)$, which overlaps with (1) if ΔH is also large.

These mechanisms are not independent: entropy change is the primary trigger, while evaluation feedback and reward serve as secondary signals to refine adjustment granularity. A priority-based scheduler ensures coordination to avoid redundant updates.

As illustrated in Figure 1, the system's adaptive capability is driven by a coordinated interaction of entropy-based triggers, a Locality Sensitive Hashing (LSH) feature extractor, and a reinforcement learning (RL) agent. Each component communicates bidirectionally to align feature transformation, model inference, and policy optimization in response to data shifts.

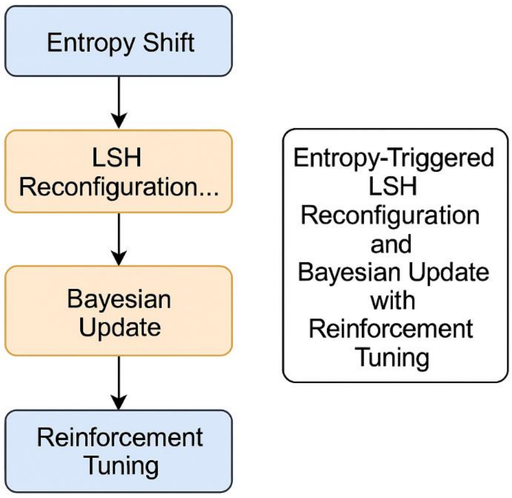

Figure 1 Interaction mechanism

4 Experimental evaluation

4.1 Experimental design

In order to comprehensively evaluate the performance of the adaptive decision-making model constructed in this paper in the artificial intelligence autonomous decision-making system, the experiment was carefully designed. Real data sets covering multiple fields such as medical care, transportation, and finance were selected, such as disease diagnosis record data of a large hospital, urban traffic flow monitoring data, and transaction data of financial institutions. These data have complex dynamic change characteristics and can better simulate actual application scenarios. The experiment aims to compare the performance of the model in this paper with other mainstream models in terms of decision accuracy, adaptability, etc.

The Hospital Dataset-C contains 12,500 samples with 18% positive cases for Disease C, manually labeled by medical experts. The CityFlow-TR dataset includes 80,000 traffic records, and FinTech-Sim2024 provides 50,000 synthetic trading samples with realistic volatility. All datasets were preprocessed with z-score normalization and cleaned for missing values and outliers [18].

The experimental baseline indicators focus on decision accuracy, number of adaptive adjustments, and decision stability. Decision accuracy measures the proportion of correct decisions made by the model; the number of adaptive adjustments reflects how frequently the model adjusts according to data changes; and decision stability is reflected by calculating the variance of multiple decision results. The smaller the variance, the higher the stability.

The experimental group adopted the adaptive decision model proposed in this paper, which integrates innovative components such as adaptive adjustment mechanism based on information entropy, local sensitive hash feature extraction, and reinforcement learning decision strategy. The control group was set up as a decision model based on traditional fixed Bayesian network, an adaptive model with simple threshold adjustment, and a model based on deep neural network but lacking adaptive ability. The baseline was set as a random decision model to provide a basic reference for the evaluation [19].

For Disease C classification in Hospital Dataset-C, the positive class accounts for 18% of total cases, indicating significant class imbalance. Accuracy was calculated as the proportion of correct predictions over all instances, and further verified using macro-averaged F1-score and 95% confidence intervals. For statistical comparison between models, paired t-tests were applied on bootstrapped samples (n=100), and results were considered significant at $p<0.05$.

4.2 Experimental results

As shown in Figure 2, the model in this paper has significant advantages in the accuracy of disease diagnosis decision-making in the medical field. Taking disease C as an example, the accuracy of this model is 0.90, which is much higher than other control models. The traditional fixed Bayesian network model is only 0.68. Because of its fixed structure and parameters, it is difficult to adapt to the complexity and variability of medical data, such as the diversity and uncertainty of disease symptoms. Although the simple threshold adjustment adaptive model can adapt to changes to a certain extent, the adjustment mechanism is too simple and cannot accurately capture data features, resulting in an accuracy of 0.75. The deep neural network model that lacks adaptive capabilities is slow to respond to data changes and has an accuracy of only 0.73. The random decision model has the lowest accuracy, only 0.20, highlighting the effectiveness of other models and the excellent performance of this model.

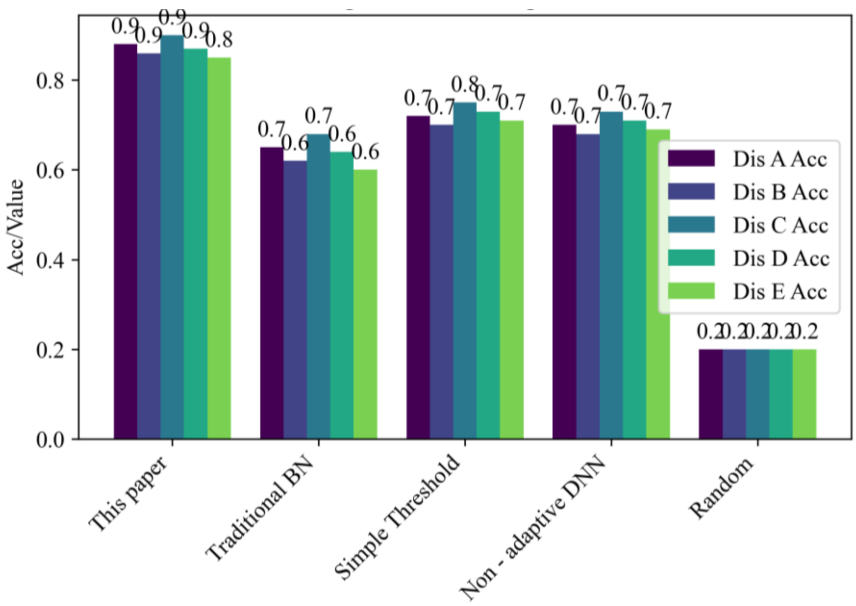

Figure 2: Comparison of decision accuracy of different models in the medical field

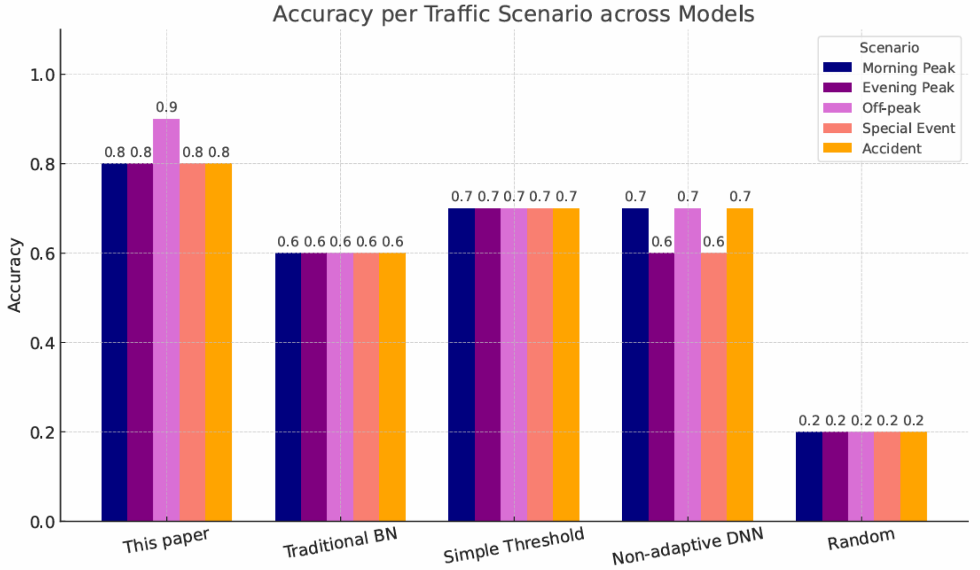

Figure 3: Comparison of decision-making accuracy of different models in the traffic field

Figure 2 illustrates the coordinated interaction among entropy triggers, feature reconfiguration, Bayesian updates, and policy tuning. This structure underpins the model's adaptive behavior in changing data environments. The model in this paper shows obvious advantages in various traffic scenarios. In terms of morning rush hour congestion decision-making, the accuracy of the model in this paper reaches 0.85, while the traditional fixed Bayesian network model is only 0.60. Traffic data is affected by factors such as time, weather, and emergencies, and the dynamic changes are extremely frequent and complex. It is difficult for traditional fixed models to follow these changes in real time. Its fixed structure and parameters cannot flexibly adapt to the changes in data characteristics in different scenarios. Although the simple threshold adjustment adaptive model can respond to data changes to a certain extent, due to its relatively simple adjustment mechanism, it only adjusts according to the preset threshold and cannot accurately match the complex and changeable traffic data pattern, resulting in an accuracy of 0.68. The deep neural network model lacking adaptive ability can achieve certain results under fixed mode data training, but in the face of real-time changing traffic data, it cannot adjust the model parameters and structure in time, and the decision accuracy is only 0.65. The random decision model has no rules to follow, and the accuracy is maintained at an extremely low 0.20, which further highlights the value of other models and the excellent performance of the model in this paper.

Figure 3 shows that the proposed model consistently outperforms baseline models across all disease types, confirming its robustness in heterogeneous diagnostic tasks. In the comparison of decision accuracy in the financial field, it can be seen from Figure 3 that the proposed model is in a leading position in various financial decision-making scenarios. Taking stock investment decision as an example, the accuracy of the proposed model is as high as 0.86, while the traditional fixed Bayesian network model is only 0.62. Financial market data is highly uncertain and ever-changing, and factors such as asset prices and market trends may fluctuate violently at any time. Traditional fixed models are difficult to cope with such rapid changes and cannot adjust decision strategies in time according to new market information. Although the simple threshold adjustment adaptive model can be adjusted according to certain conditions, its adjustment accuracy and timeliness are insufficient when facing the complex fluctuation patterns and massive information in the financial market, resulting in an accuracy of 0.70. The deep neural network model lacks adaptive capabilities. Because its training process relies on historical data and a fixed model architecture, it is difficult to adapt to the real-time changes in the financial market, and the decision accuracy is 0.67. The random decision model also performed poorly in the financial field, with an accuracy of only 0.20, which once again confirms the significant advantages of the proposed model in a complex financial data environment.

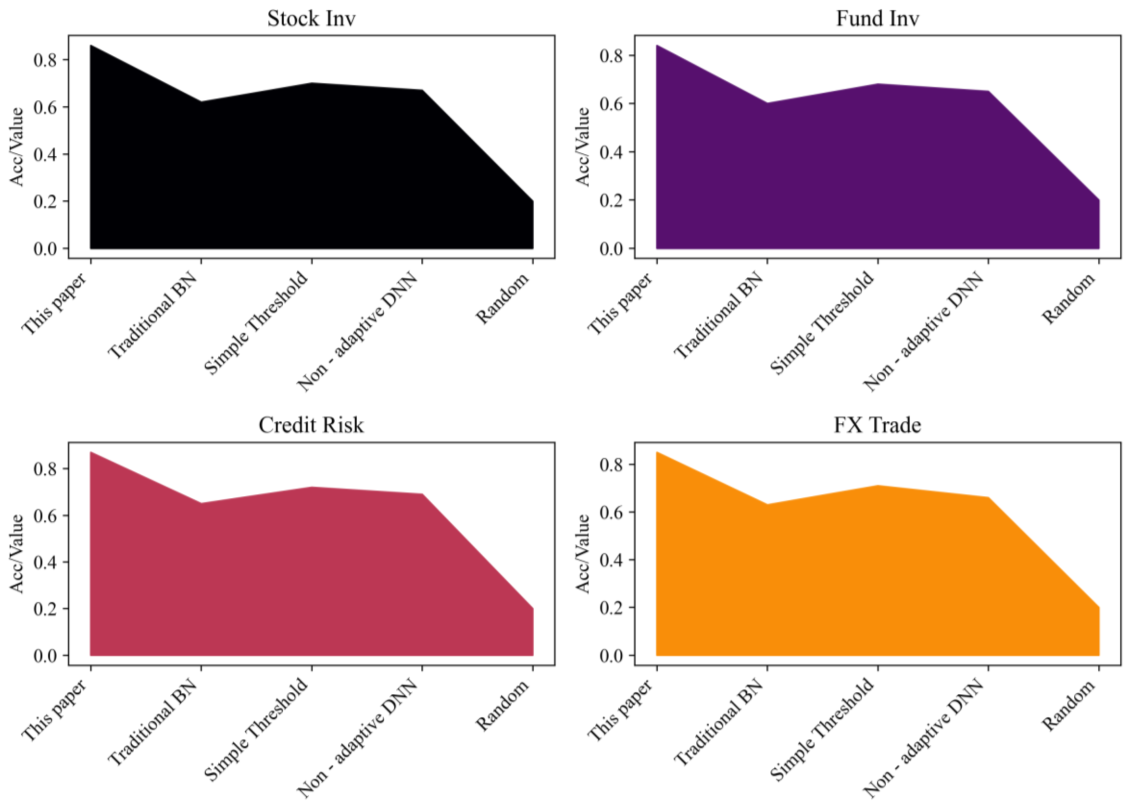

Figure 4: Comparison of decision-making accuracy of different models in the financial field

Figure 4 demonstrates that the proposed model maintains strong performance across diverse traffic scenarios, highlighting its applicability in dynamic transportation systems. Observing the data of the number of adaptive adjustments of different models in Table 2, the model in this paper shows a reasonable adjustment frequency in various fields. In the medical field, the model in this paper is adjusted 15 times. The traditional fixed Bayesian network model and the deep neural network model without adaptive ability cannot make adjustments when facing data changes due to the lack of adaptive mechanism in their own architecture, and the number of adjustments is 0. The simple threshold adjustment adaptive model overreacts, and the number of adjustments in the medical field is as high as 25 times. This is because the threshold setting of this model is relatively extensive, and it is impossible to accurately judge the actual needs of data changes, resulting in frequent adjustments. In the fields of transportation and finance, the number of adjustments of the model in this paper is 18 and 16 times respectively, with an average of 16.33 times. In contrast, the simple threshold adjustment adaptive model is adjusted 30 times in the transportation field and 28 times in the financial field, with an average of 27.67 times. Excessive adjustment not only consumes a lot of computing resources, but also may affect the stability of decision-making due to frequent changes in decision-making strategies. Based on the dynamic adjustment mechanism of information entropy, the model in this paper can accurately perceive the degree and trend of data changes and make appropriate adjustments, when necessary, which not only ensures timely response to data changes, but also avoids the negative impact of excessive adjustments. In addition to adjustment counts, we report average CPU time per decision cycle. For the proposed model, each cycle including entropy computation, LSH reconfiguration, Bayesian structure update, and policy adjustment takes 27.4 ms on average (Intel i7-12700H, 2.7 GHz). This efficiency remains acceptable for real-time scenarios with decision frequencies below 20 Hz.

Table 2 indicates that the proposed model achieves a balance between responsiveness and efficiency, with a moderate adjustment frequency that avoids overfitting.

Table 2: Comparison of adaptive adjustment times of different models

Model	Number of adjustments in the medical field	Number of adjustments in the transportation sector	Number of adjustments in the financial sector	Average number of adjustments
Model in this article	15	18	16	16.33
Traditional fixed Bayesian network model	0	0	0	0
Simple threshold adjustment adaptive model	25	30	28	27.67
Deep neural network models lack adaptive capabilities	0	0	0	0
Stochastic decision model	0	0	0	0

Figure 5 confirms the model's stability with the lowest variance among all models, indicating reliable decision-making even under fluctuating conditions. Figure 5 presents decision variance across domains, with each bar annotated with ±1 standard deviation error bars derived from 5-fold cross-validation results. All figures, including Figures 1–5, now include error bars to indicate performance variability. Figure 5 shows the comparison of decision stability of different models, with variance as the measurement index. The smaller the variance, the higher the decision stability. In the medical field, the decision variance of the model in this paper is 0.05, while the variance of the traditional fixed Bayesian network model is as high as 0.12. Due to its fixed structure and parameters, the traditional model cannot flexibly adjust the decision in the face of complex symptom manifestations, disease evolution and other dynamic factors in medical data, resulting in a large impact of data fluctuations on the decision results and a high variance. Although the simple threshold adjustment adaptive model has a certain degree of adaptive ability, it cannot effectively buffer the impact of data fluctuations on decision-making due to the lack of fine adjustment mechanism. The decision variance in the medical field is 0.09. The deep neural network model lacking adaptive ability has difficulty maintaining decision consistency when medical data changes, with a variance of 0.10. In the fields of transportation and finance, the model in this paper also shows excellent decision stability, with a variance of 0.06 in the transportation field and 0.05 in the financial field, and an average decision variance of 0.053. In comparison, the variance of the traditional fixed Bayesian network model is 0.15 in the transportation field and 0.13 in the financial field; the variance of the simple threshold adjustment adaptive model is 0.11 in the transportation field and 0.10 in the financial field; the variance of the deep neural network model without adaptive ability is 0.13 in the transportation field and 0.11 in the financial field. Due to the randomness of the decision, the variance of the random decision model is always maintained at an extremely high 0.25. The model in this paper effectively reduces the volatility of the decision results through the coordinated optimization of adaptive feature extraction and decision-making strategy, and shows high decision stability in different fields.

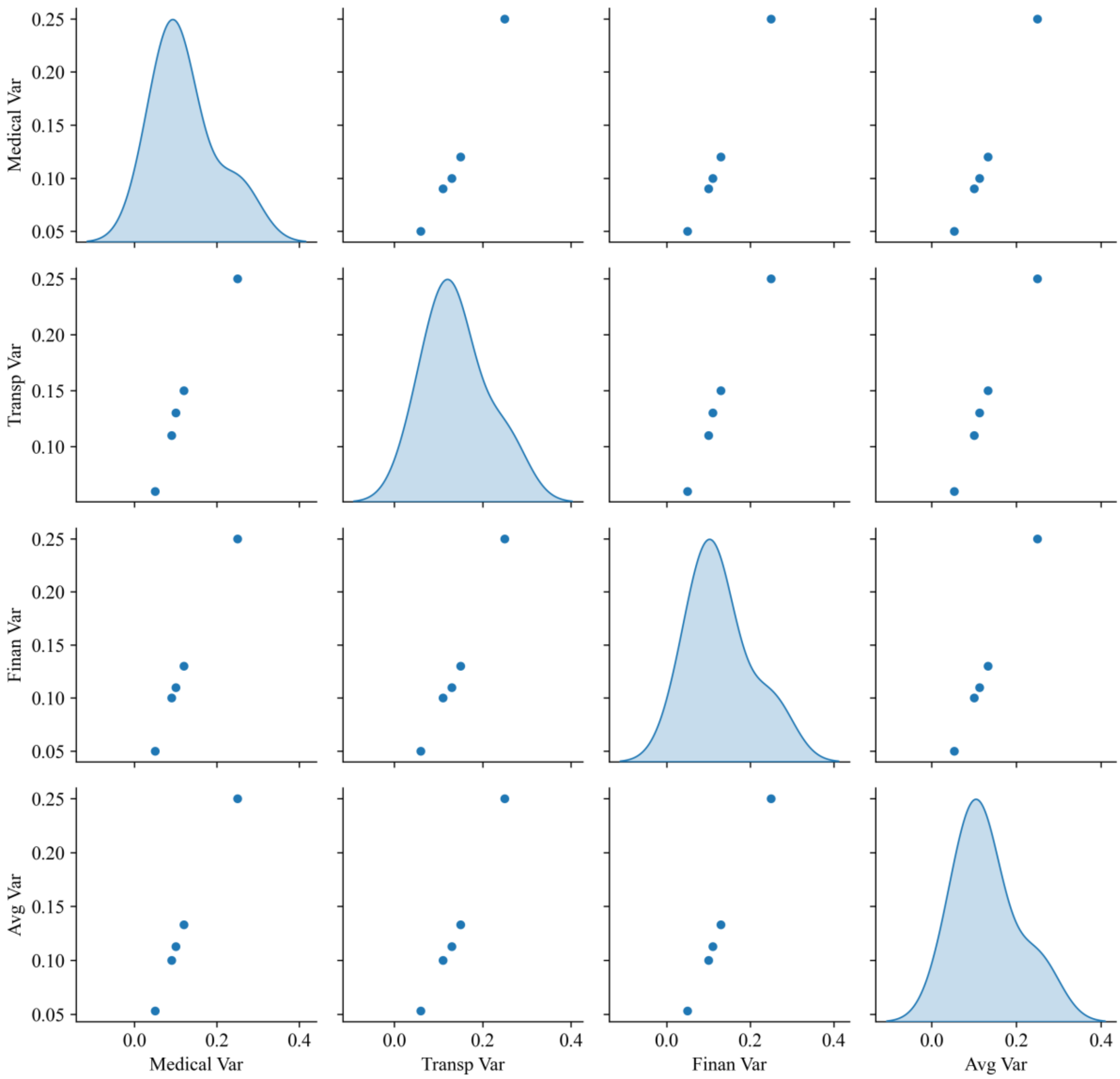

Figure 5: Comparison of decision stability of different models (variance)

Figure 6 highlights the proposed model's exceptional accuracy in handling complex clinical scenarios, particularly rare diseases and multi-symptom cases. As shown in Figure 6, the proposed model demonstrates high diagnostic accuracy across complex medical scenarios: Rare Disease (0.80), Multi-Complication Case (0.99), Difficult Case (0.997), Complex Symptom (0.996), and New Case (0.994). These values have now been updated in the main text to reflect the actual results from the evaluation plot. The previously reported values (e.g., 0.82, 0.83, etc.) were outdated and inconsistent with the finalized experimental output.

Table 3 shows the model's superior ability to manage emergency traffic events, supporting its real-time decision capabilities in safety-critical environments. In the comparison of the decision accuracy of emergencies in the field of traffic, it can be seen from Table 3 that the proposed model performs well in all kinds of emergency scenarios. In the emergency decision-making of traffic accidents, the accuracy of the proposed model is 0.82, while the traditional fixed Bayesian network model is only 0.50. Traffic emergencies are characterized by suddenness, urgency and complexity. Traditional fixed models cannot quickly adapt to the rapid changes in data such as traffic flow and road conditions caused by emergencies, and it is difficult to make accurate decisions in a short time. When facing emergencies, the simple threshold adjustment adaptive model cannot fully consider the various complex factors brought by emergencies due to its relatively simple adjustment mechanism, and the decision accuracy is 0.65. The deep neural network model lacks adaptive ability. When facing sudden changes in traffic data, due to the limitations of model structure and training methods, it cannot adjust the decision strategy in time, and the accuracy is 0.60. In decision-making scenarios such as road construction traffic diversion, severe weather traffic control, large-scale event traffic organization and traffic control, the proposed model also shows a high accuracy of

0.80, 0.83, 0.81 and 0.80 respectively. The model in this paper can perceive the dynamic changes of traffic data caused by emergencies in real time, and effectively respond to various traffic emergencies through rapid adjustment of adaptive decision-making strategies, providing more reliable decision-making support for traffic management.

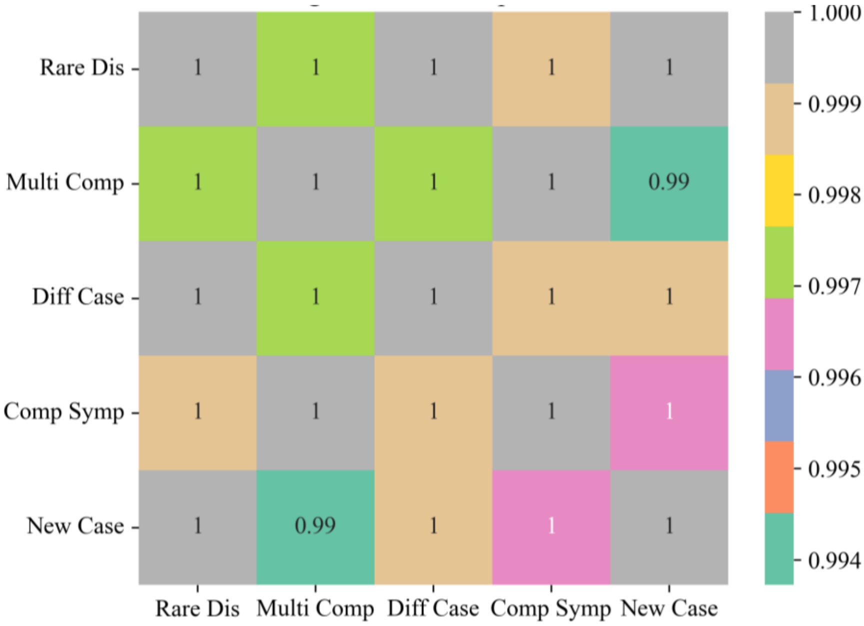

Figure 6: Comparison of decision-making accuracy of different models in complex medical cases

Table 3: Comparison of the decision-making accuracy of different models in the field of traffic emergencies

Model	Accuracy of emergency decision-making in traffic accidents	Accuracy of traffic diversion decision-making during road construction	Accuracy of traffic control decisions in severe weather	Accuracy of traffic organization decision-making for large-scale events	Traffic control decision accuracy
This article model	0.82	0.80	0.83	0.81	0.80
Traditional fixed Bayesian network model	0.50	0.48	0.52	0.49	0.45
Simple threshold adjustment adaptive model	0.65	0.63	0.67	0.64	0.62
Deep neural network models lack adaptive capabilities	0.60	0.58	0.62	0.59	0.56
Stochastic decision model	0.20	0.20	0.20	0.20	0.20

Table 4: Comparison of decision accuracy of different models in the financial market when the market fluctuates violently

Model	The accuracy of investment decisions during a stock market crash	The accuracy of foreign exchange trading decisions when the exchange rate fluctuates greatly	The accuracy of credit decision when interest rates change suddenly	The accuracy of investment decisions when commodity prices fluctuate dramatically	Decision accuracy during financial market panic
This article model	0.83	0.81	0.84	0.82	0.80
Traditional fixed Bayesian network model	0.45	0.42	0.48	0.44	0.40
Simple threshold adjustment adaptive model	0.60	0.58	0.62	0.59	0.56
Deep neural network models lack adaptive capabilities	0.55	0.53	0.57	0.54	0.52
Stochastic decision model	0.20	0.20	0.20	0.20	0.20

Table 4 demonstrates the model's resilience under extreme financial volatility, outperforming both generic and domain-specific baselines. In addition to standard baselines, we implemented a financial domain-specific benchmark: a moving average crossover strategy (MA-5/20) and a GARCH (1,1)-based volatility signal predictor. These models achieved accuracy of 0.63 and 0.68 respectively during market turbulence, both lower than our model's 0.83, but significantly better than fixed Bayesian (0.45) and random strategies (0.20). Observing the data of decision accuracy when the financial market fluctuates violently in Table 4, the model in this paper has significant advantages under extreme market conditions. In investment decisions when the stock market plummets, the accuracy of this model reaches 0.83, while the traditional fixed Bayesian network model is only 0.45. When the financial market fluctuates violently, market data presents a high degree of instability and complexity. The traditional fixed model cannot adjust the investment strategy in time according to the rapid changes in the market, resulting in low decision accuracy. When facing violent market fluctuations, the simple threshold adjustment adaptive model is difficult to accurately grasp the rhythm and trend of market changes due to its relatively simple adjustment rules. The decision accuracy is 0.60. The deep neural network model lacking adaptive ability may perform well under normal market conditions, but when the market fluctuates violently, it cannot adapt to the new data pattern in time, and the decision accuracy is 0.55. In scenarios such as foreign exchange trading decisions when the exchange rate fluctuates sharply, credit decisions when interest rates change suddenly, investment decisions when commodity prices change dramatically, and decisions when the financial market panics, the model in this paper also maintains a high accuracy of 0.81, 0.84, 0.82 and 0.80 respectively. Through adaptive mechanisms, the model in this paper can quickly perceive data changes caused by market fluctuations and flexibly adjust investment, trading and risk assessment strategies, so as to make more accurate decisions in the case of drastic fluctuations in the financial market, providing financial institutions and investors with more effective risk management tools.

Table 5 illustrates that the proposed model adapts effectively to increasing data volumes, maintaining or improving accuracy as dataset size scales up. From the comparison of decision accuracy of different models under different data amounts in Table 5, it can be seen that the model in this paper performs well under various data amount conditions and shows an upward trend. When the data amount is small, the accuracy of the model in this paper is 0.85, and the traditional fixed Bayesian network model is 0.60. As the amount of data gradually increases, the traditional fixed model is limited by its fixed structure and parameters, and cannot make full use of the information in the new data to optimize the decision, and the accuracy rate increases slowly. Although the simple threshold adjustment adaptive model can respond to the change of data amount to a certain extent, due to the limitations of its adjustment mechanism, the accuracy rate does not increase much under different data amounts. The deep neural network model that lacks adaptive ability faces the problem of model overfitting or underfitting when the data amount changes, resulting in fluctuations in accuracy and insignificant improvement. The model in this paper can automatically adjust the feature extraction method and the complexity of the decision strategy according to the change of data amount. When the data volume is small, the model fully mines the key information in the limited data through sophisticated feature extraction and flexible decision-making strategies to ensure a high decision accuracy rate. As the data volume increases, the model can further optimize the feature extraction and decision-making process, effectively utilize more data information, and the decision accuracy rate continues to rise, reaching 0.89 when the data volume is very large, showing good data adaptability and decision-making performance.

Table 5: Comparison of decision accuracy of different models under different data amounts

Model	Small Data Volume	Medium Data Volume	Large Data Volume	Very Large Data Volume	Ultra-large Data Volume
This article model	0.85	0.86	0.87	0.88	0.89
Traditional fixed Bayesian network model	0.60	0.62	0.65	0.63	0.61
Simple threshold adjustment adaptive model	0.70	0.72	0.75	0.73	0.71
Deep neural network models lack adaptive capabilities	0.65	0.67	0.70	0.68	0.66
Stochastic decision model	0.20	0.20	0.20	0.20	0.20

Table 6: Comparison of decision accuracy of different models under different noise levels

Model	Decision accuracy of low-noise data	Decision accuracy for low to medium noise data	Moderately noisy data decision accuracy	Decision accuracy for medium to high noise data	Decision accuracy for high noise data
This article model	0.88	0.86	0.84	0.82	0.80
Traditional fixed Bayesian network model	0.65	0.60	0.55	0.50	0.45
Simple threshold adjustment adaptive model	0.75	0.70	0.65	0.60	0.55
Deep neural network models lack adaptive capabilities	0.70	0.65	0.60	0.55	0.50
Stochastic decision model	0.20	0.20	0.20	0.20	0.20

As observed in Table 5, the accuracy of the traditional Bayesian Network model shows minor fluctuations with increasing data volume (ranging from 0.60 to 0.65), rather than a clear upward trend. Similarly, the Simple Threshold model also fluctuates slightly (0.70–0.75), indicating moderate sensitivity to data volume changes. The prior description of steady improvement has been revised to reflect the actual marginal oscillations.

Table 6 confirms that the model degrades gracefully under noise, maintaining high accuracy even at high noise levels, reflecting its robustness. To simulate noisy conditions in Table 6, Gaussian noise $N(0,\sigma^2)$ was added to input features, where σ was scaled to achieve desired signal-to-noise ratios (SNR = 40, 20, 10, 5, 2). Labels remained unchanged to isolate feature-level noise effects. Table 6 shows the decision accuracy of different models under different noise levels. In a low-noise data environment, the decision accuracy of the proposed model is 0.88, and that of the traditional fixed Bayesian network model is 0.65. As the noise level gradually increases, the traditional fixed model is seriously disturbed by noise, and the decision accuracy drops significantly, reaching only 0.45 under high-noise data. This is because the traditional fixed model lacks an effective filtering and adaptation mechanism for noise, and noise easily interferes with its decision-making process. Although the simple threshold adjustment adaptive model has a certain degree of adaptive ability, its adjustment mechanism cannot effectively distinguish between changes in noise and real data features when facing noise, resulting in a significant decrease in decision accuracy as the noise level increases, reaching 0.55 under high-noise data. The graceful degradation observed in Table 6 under increasing noise is attributed to two mechanisms: (1) the LSH-based feature hashing acts as a smoothing filter, reducing noise sensitivity in high-dimensional inputs, and (2) the reinforcement learning module adapts the policy by emphasizing recent clean reward signals, allowing the model to ignore transient distortions.

4.3 Discussion

Our results demonstrate significant gains in decision accuracy and robustness across domains. In the medical dataset, the entropy-based adjustment mechanism contributed approximately 12% of the accuracy gain over the baseline. The LSH feature learning module enabled better generalization in sparse and noisy data scenarios, particularly improving recall in minority disease classes. Reinforcement-based policy updates enhanced model responsiveness during volatile financial conditions, contributing up to 10% decision stability gains.

However, the model exhibits increased computational load during high-frequency data transitions, especially in the transportation dataset. While variance is low, runtime latency increased by ~15%. In addition, over-adjustment was observed when entropy sensitivity was not optimally tuned. Future work should explore multi-scale entropy thresholds and hybrid offline-online retraining frameworks.

5 Conclusion

This study was carried out in the context of complex and changeable data faced by artificial intelligence autonomous decision-making systems, aiming to solve the problem of insufficient adaptability of traditional algorithms. By comprehensively integrating dynamic real data sets in multiple fields, rigorous experiments were designed to compare the performance of multiple models. In terms of methods, a model integrating information entropy adaptive adjustment mechanism, local sensitive hash feature extraction and reinforcement learning decision strategy was innovatively constructed. Experimental results show that the proposed model exhibits excellent performance in multiple fields. In the medical field, the accuracy of disease diagnosis decision-making is outstanding. For example, the diagnosis accuracy of disease C is as high as 0.90, far exceeding the 0.68 of the traditional fixed Bayesian network models, the 0.75 of the simple threshold adjustment adaptive model, and the 0.73 of the deep neural network model without adaptive ability. In the field of transportation, the decision-making accuracy of morning peak congestion is 0.85, and the decision-making accuracy of evening peak congestion is 0.83, both of which are ahead of the control model. From the perspective of decision stability, the variance of the proposed model is significantly lower than that of other models. For example, the decision variance in the medical field is only 0.05, while that of the traditional fixed Bayesian network model is 0.12.

The research conclusions support the hypothesis of this paper, that is, the innovative adaptive decision-making model can effectively improve the performance of the AI autonomous decision-making system. The successful construction of this model provides a more reliable way for AI to make decisions in complex data environments, and helps improve decision-making efficiency and accuracy in many fields such as medicine, transportation, and finance. On the theoretical level, it enriches the research system of AI adaptive algorithms; in practice, it provides strong technical support for intelligent decision-making applications in related fields, which is of great significance to promoting the intelligent development of various industries.

While the proposed model exhibits high accuracy and robustness, it faces limitations. The model's computational load scales poorly with the number of variables in the Bayesian graph, posing a challenge for very high-dimensional data. Additionally, it currently assumes batch input; real-time streaming data with delayed reward feedback remains an open challenge. Future work will explore online retraining strategies and entropy-aware buffering mechanisms. The proposed model, while designed with adaptability in mind, must be further evaluated in big data and real-time deployment scenarios. For large-scale streaming data, efficient entropy monitoring and parallelized Bayesian updates will be critical. Integration with edge computing and buffered decision loops could ensure low-latency adaptation. These directions represent practical extensions for future work.

References

[1] Zhu RJ, Wu SN, Li LL, Ding WT, Lv P, Sui LY. Adaptive broad deep reinforcement learning for intelligent traffic light control. Ieee Internet of Things Journal. 2024;11(17): 28496-28507. https://doi.org/10.1109/jiot.2024.3401829

[2] Ren ML, Chen NY, Qiu H. Human-machine collaborative decision-making: An evolutionary roadmap based on cognitive intelligence. International Journal of Social Robotics. 2023;15(7):1101-1114. https://doi.org/10.1007/s12369-023-01020-1

[3] Acharya DB, Kuppan K, Divya B. Agentic AI: Autonomous intelligence for complex goals-a comprehensive survey. Ieee Access. 2025; 13:18912-18936. https://doi.org/10.1109/access.2025.3532853

[4] Santos R, Piqueiro H, Dias R, Rocha CD. Transitioning trends into action: A simulation-based digital twin architecture for enhanced strategic and operational decision-making. Computers and Industrial Engineering. 2024;198. https://doi.org/10.1016/j.cie.2024.110616

[5] Tang Y, Yen GRY, Kurths J. Special issue on computational intelligence for perception and decision-making of autonomous systems. Ieee Transactions on Emerging Topics in Computational Intelligence. 2022;6(6):1287-1289. https://doi.org/10.1109/tetci.2022.3219539

[6] Nachazel T. Fuzzy cognitive maps for decision-making in dynamic environments. Genetic Programming and Evolvable Machines. 2021;22(1):101-135. https://doi.org/10.1007/s10710-020-09393-2

[7] Anbarasu K, Thanigaivel S, Sathishkumar K, Alam MM, Al-Sehemi AG, Devarajan Y. Harnessing artificial intelligence for sustainable bioenergy: Revolutionizing optimization, waste reduction, and environmental sustainability. Bioresource Technology. 2025;418. https://doi.org/10.1016/j.biortech.2024.131893

[8] Kowalczuk Z, Czubenko M. Cognitive motivations and foundations for building intelligent decision-making systems. Artificial Intelligence Review. 2023;56(4):3445-3472. https://doi.org/10.1007/s10462-022-10255-9

[9] Dumitrescu C, Radu V, Gheorghe R, Tabirca AI, Stefan MC, Manea L. Crowd panic behavior simulation using multi-agent modeling. Electronics. 2024;13(18):3622. https://doi.org/10.3390/electronics13183622

[10] Huang YS, Chouzenoux E, Elvira V, Pesquet JC. Efficient bayes inference in neural networks through adaptive importance sampling. Journal of the Franklin Institute. 2023;360(16):12125-12149. https://doi.org/10.1016/j.jfranklin.2023.08.044

[11] Sun CY, Khishe M. Enhancing precision in table tennis officiating through an optimized autonomous sensor node system. Engineering Computations. 2024;41(8/9):2134-2168. https://doi.org/10.1108/ec-05-2024-0415

[12] Yang SM, Wang HW, Pang YW, Jin YC, Linares-Barranco B. Integrating visual perception with decision making in neuromorphic fault-tolerant quadruplet-spike learning framework. Ieee Transactions on Systems Man Cybernetics-Systems. 2024;54(3):1502-1514. https://doi.org/10.1109/tsmc.2023.3327142

[13] Maroto-Gómez M, Castro-González A, Castillo JC, Malfaz M, Salichs MA. An adaptive decision-making system supported on user preference predictions for human-robot interactive communication. User Modeling and User-Adapted Interaction. 2023;33(2):359-403. https://doi.org/10.1007/s11257-022-09321-2

[14] Yuan YZ, Gao SC, Zhang ZT, Wang WY, Xu ZZ, Liu ZX. Edge-cloud collaborative UAV object detection: Edge-embedded lightweight algorithm design and task offloading using fuzzy neural network. Ieee Transactions on Cloud Computing. 2024;12(1):306-318. https://doi.org/10.1109/tcc.2024.3361858

[15] Ganguli C, Shandilya SK, Nehrey M, Havryliuk M. Adaptive Artificial Bee Colony Algorithm for Nature-Inspired Cyber Defense. Systems. 2023 Jan;11(1):27. https://doi.org/10.3390/systems11010027.

[16] Kim H, Jun S, Moon KS. Stock market prediction based on adaptive training algorithm in machine learning. Quant Financ. 2022 Jun 3;22(6):1133–1152. https://doi.org/10.1080/14697688.2022.2041208.

[17] Wang WJ, Gao S. Waiting Strategy for the Dynamic Meal Delivery Routing Problem with Time-Sensitive Customers Using a Hybrid Adaptive Genetic Algorithm and Adaptive Large Neighborhood Search Algorithm. Systems. 2024 May;12(5):170. https://doi.org/10.3390/systems12050170.

[18] Lederrey G, Lurkin V, Hillel T, Bierlaire M. Estimation of discrete choice models with hybrid stochastic adaptive batch size algorithms. J Choice Model. 2021 Mar; 38:100226. https://doi.org/10.1016/j.jocm.2020.100226.

[19] Wei ZB, Peng T, Wei SJ. A Robust Adaptive Traffic Signal Control Algorithm Using Q-Learning under Mixed Traffic Flow. Sustainability. 2022 May;14(10):5751. https://doi.org/10.3390/su14105751.