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Research Article

Global Economic Market Forecast and Decision System for IoT and Machine Learning

Biao Liu and Zhipeng Sun

Business School, China University of Political Science and law, Beijing, 100088 Beijing, China

Correspondence should be addressed to Zhipeng Sun; 1902060205@cupl.edu.cn

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The fast growth of IoT in wearable devices, smart sensors, and home appliances will affect every aspect of our lives. With the rapid development of economic globalization, how to integrate science and technology into economic decision-making is the focus of the current research field, and the research of this paper is precisely to solve this problem. This paper proposes a global economic market forecasting and decision-making system research based on the Internet of Things and machine learning. Using the wireless sensor network of the Internet of Things technology to perceive and predict the global economic market, through the decision tree method in machine learning, and combine the global economic market to make economic decisions, this paper explores the decision tree algorithm with the highest execution efficiency through the experimental comparison of four decision tree algorithms: ID3 algorithm, C4.5 algorithm, CART algorithm, and IQ algorithm. The output of the experiments in the paper indicates that the C4.5 algorithm has the fastest running speed. When the dataset increases to 110,000, its running time reaches 503 s.

1. Introduction

From the first day of its birth, the Internet of Things (IoT) has been regarded as a web that links anything to the web for message interchange and collaboration for smart recognition, location, monitoring, and control [1]. The way of data automatic perception and collection adopted by the Internet of Things has generated big data. Such big data cannot be analyzed and processed manually by traditional data analysis methods. The way to make IoT data analysis and processing smarter is to apply machine learning to it. Machine learning (ML) systems automatically learn models from training data and use them to predict the value of future data. They are widely used in many fields [2, 3]. For example, it can be seen in data mining, computer vision, natural language processing, medical diagnosis, and other fields. A recent study in machine learning concluded that large-scale datasets can be used to replace complexity in modeling. With the explosion of large-scale data and advances in processing infrastructures for large-scale data, this insight has resulted in massive machine learning implementations and facilitated the uptake of ML in many areas of use. Macro data forecasting is the basic skill of economic research, and it is also a "wind vane" for grasping the macro trend and market development. It can be seen that global economic market forecasts and decision-making are crucial to promoting global economic development. Since the world entered the post-financial crisis era, the world economic market has entered the bottom, and it has been slow to recover and get out of the predicament. Therefore, in the research on global economic market forecasting and decision-making system, its future development trend has attracted more and more attention. At the same time, it is imperative to apply machine learning to the global economic market decision-making system.

Machine learning can teach machines to learn like humans from previous experience and apply machine learning algorithms to global economic market decision-making, bringing new opportunities and challenges to the development of global economic market forecasting. The role of machine learning in IoT data detection and perception is critical. This paper conducts in-depth research on global economic market forecasting and decision-making based on the IoT and machine learning to promote the development of the global economy.

In latest years, many experts and researchers have mainly focused on the research of Internet of Things techniques and machine learning, but they have not paid much attention to the global economic market forecast. They only talked about the advantages of machine learning in economic market forecasting from the side and lacked specific conceptual research and practical exploration. Therefore, this paper studies the global economic market forecasting and decision-making system based on the Internet of Things and machine learning, so as to promote the development of Internet of Things technology and machine learning, which also provides reference for future related research on global economic market forecasting.

2. Related Work

The Internet of Things has huge market potential, and the growth rate has been increasing in recent years. Today, various systems for the real-time prediction have been created using the IoT. The main task of this development is to forecast a wide range of parameters of space conditions as precisely as possible using suitable prediction models. In this study, Dabbakuti proposed an ionospheric Internet of Things analysis system with variational mode decomposition (VMD) based on nuclear limit learning machine (KELM). ThingSpeak data is provided to the ionospheric prediction model. The results projected from the suggested version of the model enable a quicker drilling process and achieve similar precision to that of the VMD ANN [4]. The IoT, which incorporates various appliances into a network to deliver high-level smart services, must preserve user confidentiality and address deception attacks, denial-of-service (DoS) assaults, tampering, and wiretapping, among other attacks. Therefore, Xiao studied the attack model of the Internet of Things system and reviewed the Internet of Things (IoT) safety measures based on ML solutions, such as monitored learning, not-supervised learning, and reinforcement learning (RL) [5]. To assure data security and stability, Physical Unlatable Features (PUFs) have been established as low-weight, workable safety protocols in the IoT frameworks, problematic to clone PUF-based edge nodes in different settings, such as unencrypted, encrypted, and obfuscated challenges in IoT frameworks [6]. Opportunistic IoT (OppIoT) networks are a subcategory of IoT networks where connectivity between origin and target appliances is episodic. Vashishth works on leveraging machine learning (ML) to drive automated ranging decision-making in OppIoT. To perform this, a proposed ranging technique, referred to as GMMR, is developed using a Haussian Hybrid Method, an ML-based soft clustering mechanism. The design of GMMR incorporates the benefits of context aware and concept independent ranging protocols. The capabilities of GMMR are compared with those of KNNR, HBPR, and MLPROPH and PROPHET. The simulation results show that it surpasses all these mentioned cabling protocols in every single aspect of performance [7]. Traditional machine learning based methods need sophisticated and costly on-chip data collection framework to run hardware Trojan horse detection, which will lead to high area and power overhead. In order to meet these challenges, Khalid uses the power correlation between microprocessor execution instructions to establish a runtime hardware Trojan horse (HT) detection framework based on machine learning, called MacLeR. Pilot tests show that in comparison to cutting-edge HT inspection techniques, MacLeR improves HT inspection precision by 10% (i.e., 96.256%) while enabling a reduction in area and weight savings of overhead by a factor of 7 [8]. The innovation of the IDS (Intrusion Detection System) design has a crucial part in ensuring the safety of the Industrial IoT. Yao investigated the typical studies on IDS testing techniques and system structure in recent years. In addition, a mixed IDS infrastructure is proposed, and an ML-assisted inspection approach is introduced, which is superior to the literature in a series of benchmark tests [9]. In summary, the combination of IoT approach and ML approach has been applied to different fields, including real-time prediction system and IoT security. The process of economic globalization is also accelerating. While countries around the world are committed to economic development, there is not much research on the combined use of IoT and ML technology in the global economic market prediction and decision-making system, so more in-depth exploration is needed.

3. Theories Related to Global Economic Market Forecasting and Decision-Making System Research Based on the Internet of Things and Machine Learning

3.1. IoT Technology. The IoT technology refers to data transmission in accordance with specific standards through high-tech means such as tracking and positioning technology and laser scanning technology. It connects real objects to realize intelligent information technology. In the global economic market, the IoT realizes real-time forecasting of the global economic market through the network [10, 11].

After computers and the Internet, the value of the Internet of Things in the world's third information technology revolution will be 30 times that of the Internet. The IoT is an upgraded version of the Internet, which can also be said to be composed of multiple Internet connections. It is based on the Internet and expands the client side towards the physical world, so as to conduct communication and data exchange as a network [12, 13]. The use of the IoT technology can be achieved through three steps: Step 1, use various sensing devices and technologies to perceive various object information, so as to achieve ubiquitous perception; Step 2, no matter what environment and place, no matter what network or application system, it can be accessed through wired or wireless means, so as to realize interconnection and information sharing; and Step 3, provide different information services according to the needs of different users, and additionally provide some intelligent processing and auxiliary decision-making to achieve intelligent services. The technical framework of the IoT is mostly composed of 3 floors, which are sensing layer, networking layer, and usage layer. The network layer mainly transmits the obtained information to the backend server through the Internet; the IoT perception layer is the foundation of the IoT network, which consists of various devices with perception capabilities. Finally, the application layer processes the information obtained by the front-end perception layer to realize the application, for example, environmental monitoring, location services, and other practical applications [14, 15]. The basic architecture of the IoT is illustrated in Figure 1.

3.2. The Concept of Forecast and Global Economic Market Forecast. The so-called prediction, which refers to predetermining or guessing, of course, is not a conjecture or an unfounded judgment; instead, it adopts certain forecasting techniques and uses certain logical thinking and scientific methods to estimate and infer the future development trend and changing laws of things according to the past and present of things. It judges the change law and development trend of things in the future through the current trend and the law of the past [16, 17].

Global economic market forecast is to grasp the development of the overall economy. The research on global economic market forecast is more complicated and arduous than other specific market economic forecasts. This is not only because the factors affecting the changes in the global economic market include not only economic factors such as the world economy and other fields, but also political factors such as national or regional government policies, regional conflicts, and stability [18].

3.3. Decision Tree Algorithm. One of the important cores of artificial intelligence research is machine learning, through which computers can perform learning activities like humans. This can not only continuously acquire new knowledge and improve this knowledge, but also gradually improve this knowledge systematically. There are many inductive learning methods in machine learning, which are mainly used for model building prediction and classification data [19, 20]. Currently, machine learning is helping in many aspects in global economic market decision-making, such as smart irrigation and rainfall forecasting. There are many predictive models in machine learning, and decision trees are one of them. It is a machine learning algorithm capable of solving classification or regression problems. A test on an attribute in a decision tree is usually represented by an internal node; the final category is represented by leaf nodes, because the decision tree model can restore the decision-making process very well. It decomposes the complicated policy-making procedure into a range of easy options, which can better interpret the entire decision-making procedure [21]. So, determination tree-based methods are employed to address many issues, for example, optimization and table lookup.

The decision tree consists of 3 parts: non-leaf nodes, wings, and leaves. Each of the non-leaf nodes represents an attribute, each leaf node represents a category, and the root node is the first non-leaf node of the decision tree; the attribute value of one of the attributes is represented by each branch. Most decision trees expand outward with the root node as the knowledge point, and each attribute may form two branches, or even more, so there will be different results. If its generation process is plotted as a picture, it is like the shape of a tree, and the name of the decision tree is also derived from it [22, 23]. A decision tree structure is shown in Figure 2.

The main work of the decision tree operator is to define the structure between attributes and form a decision-making tree [24]. There are two steps in the decision-making tree construction process: decision-making tree generation and decision tree pruning, as shown in Figure 3. Precutting and postcutting are two popular approaches to pruning. Generally speaking, postpruning is more computationally intensive than prepruning, because prepruning is performed during the formation of the decision tree. When the node satisfies the pruning condition, the formation of the branch will be stopped by setting the depth value of the decision tree. Then, pruning is done after the decision tree is generated. Postpruning needs to determine whether the node needs to be pruned by judging whether the pruned node affects the accuracy of the decision tree prediction. Therefore, the postpruning method is adopted in this paper.

Its construction process can be exemplified. For example, the fault characteristic attribute of a signal equipment of an enterprise is A_1, A_2, A_3, the attribute values are 1 and 2, and the fault type is F_1, F_2, F_3; the fault samples are shown in Table 1. This fault sample generates a simple decision tree through a decision tree. As shown in Figure 4.

The decision tree algorithm needs to be used in the formation process of the decision tree. The common decision tree algorithms include ID3, C4.5, CART, and IQ algorithm [25, 26]:

(1) The ID3 algorithm uses the attributes of information gain as nodes and creates different branches to achieve the purpose of forming a decision tree. The depth of the decision tree generated by the ID3 algorithm is not high, but the accuracy rate is good, and the formed decision tree is easy to understand. Its disadvantages are as follows:

(a) Preference to select attributes with a large number of attribute values, but this attribute is often not the best attribute

(b) The ability to express concise logic is not very good, and the correlation between the attributes of the generated decision tree is weak

(c) The decision tree will change with the increase of training samples, which is not conducive to progressive learning

(d) Difficulty dealing with continuous attributes

(2) The C4.5 algorithm is an algorithm extended on the basis of the ID3 algorithm. The weakness of this

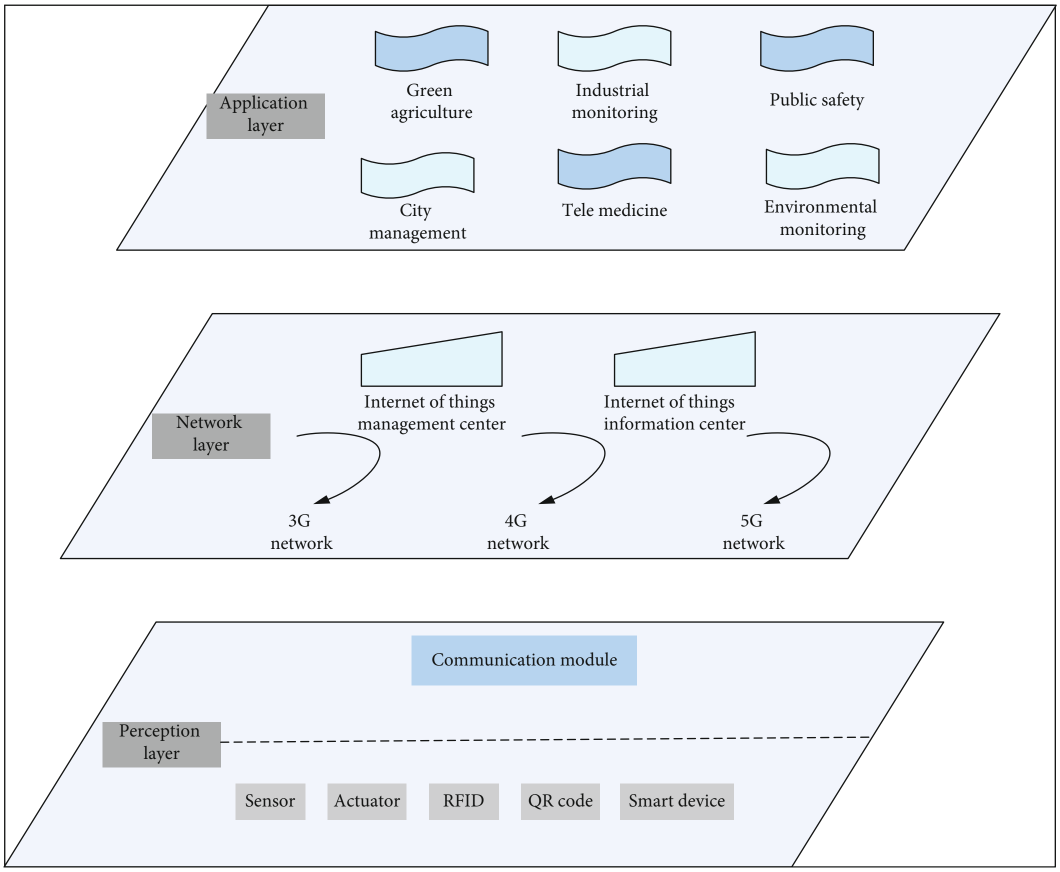

Figure 1: Basic architecture diagram of the Internet of Things.

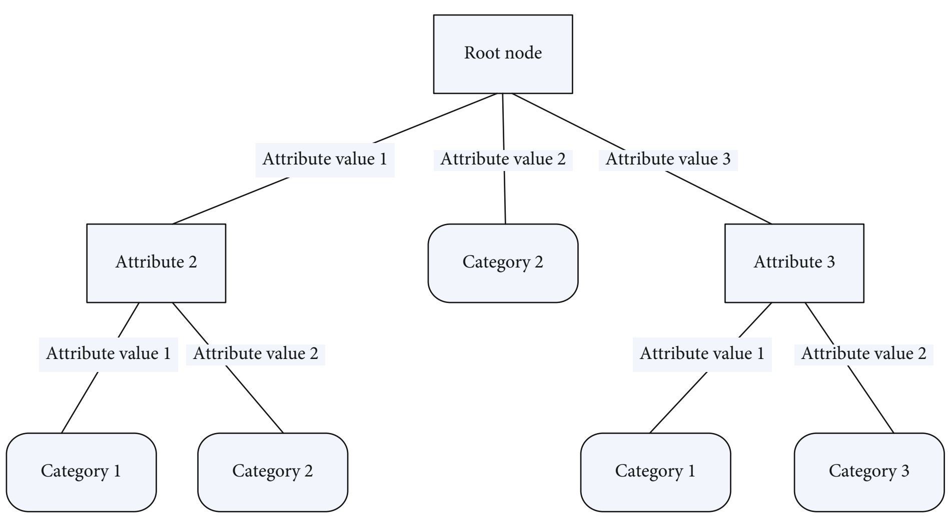

Figure 2: Schematic diagram of decision tree structure.

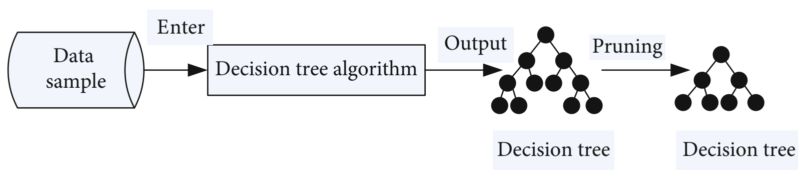

Figure 3: Schematic diagram of decision tree construction.

Table 1: Fault samples.

Property A_1	Property A_2	Property A_3	Fault type
1	1	2	F_1
1	1	1	F_1
1	2	1	F_2
2	2	1	F_3

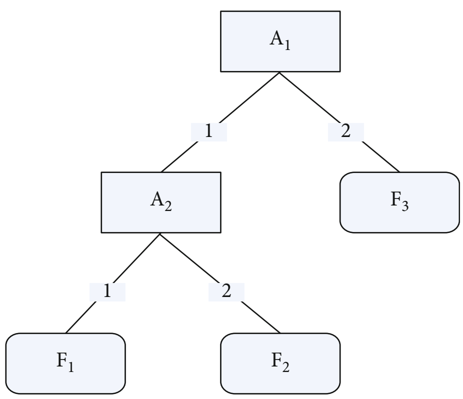

Figure 4: Generated simple decision tree.

approach is that the data needs to be operated many times in the decision tree formation and the algorithm efficiency is not very prominent, as shown in Figure 5. Its advantages are as follows:

(a) Like the ID3 algorithm, the accuracy rate is high

(b) There is a basis for selecting attributes

(c) It can handle the discretization of continuous attributes better

The specific steps of the C4.5 algorithm include discretization processing, information gain of operation attributes, recursive calculation of the maximum information gain rate attribute, calculation of attribute information gain rate, decision tree pruning, and extraction of decision rules. Its calculation formula is shown in Formula (1)-Formula (20):

$$p_i = \frac{|D_i|}{|D|}\ i = 1, 2, \cdots, k, \tag{1}$$

$$Entropy(D) = -\sum_{i=1}^{k} p_i \log_2(p_i), \tag{2}$$

where D indicates the data sample after discretization and k indicates the total number of categories of data samples after discretization.

$$p_{ij} = \frac{|D_{Aij}|}{|D_{Aj}|}\ j = 1, 2, \cdots, m\,; i = 1, 2, \cdots, k, \tag{3}$$

$$Entropy(A = v_j) = -\sum_{i=1}^{k} p_{ij} \log_2\left(p_{ij}\right), \tag{4}$$

$$Entropy(A) = -\sum_{j=1}^{m} \frac{|D_{Aj}|}{|D|} \times Entropy(A = v_j), \tag{5}$$

$$Gain(A) = Entropy(D) - Entropy(A), \tag{6}$$

where A indicates attributes and i represents the category in the data sample.

$$p_j = \frac{|D_{Aj}|}{|D|} (j = 1, 2, \cdots, m), \tag{7}$$

$$H(A) = -\sum_{j=1}^{m} p_j \log_2\left(p_j\right), \tag{8}$$

$$GainRaito(A) = \frac{Gain(A)}{H(A)}, \tag{9}$$

where $H(A)$ represents the information entropy of attribute A and $H(A)$ indicates the information gain rate of attribute A.

$$f\left|\frac{f - f^e}{\sqrt{f^e(1 - f^e)/N}} > \mu_1 - \alpha\right| = \alpha, \tag{10}$$

$$e = \frac{f + \left(z^2/2N\right) + z\sqrt{f/N - \left(f^2/N\right) + \left(z^2/4N^2\right)}}{1 + \left(z^2/N\right)}\ z = 1 - \mu_{1-\alpha}, \tag{11}$$

where $f = E/N$ indicates the actual false positive rate of the training sample; N indicates the total number of samples of the pruned tree; and α indicates the calculated result value.

Before using the C4.5 algorithm to process sample data, observe the data. If the attribute has continuous values, it is

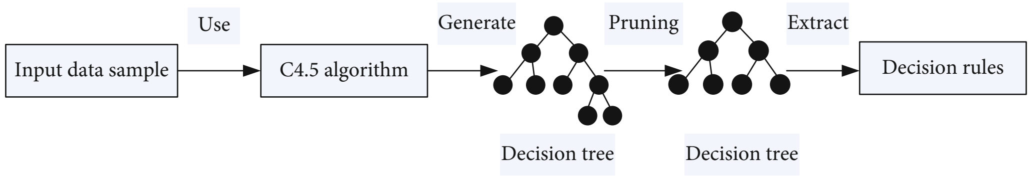

FIGURE 5: Schematic diagram of the algorithm.

TABLE 2: Dataset description.

Serial number	Dataset name	Total number of instances	Number of attributes	Number of class labels	With or without missing values
1	CMC	1584	6	15	N/A
2	Magic	20130	12	2	No
3	Chess	29167	7	19	No
4	Higgs	220000	23	2	N/A
5	Robotnavigation	6567	4	9	N/A
6	Letter	30000	17	3	No
7	Vowel	1100	11	3	No
8	Aggregation	899	3	13	No

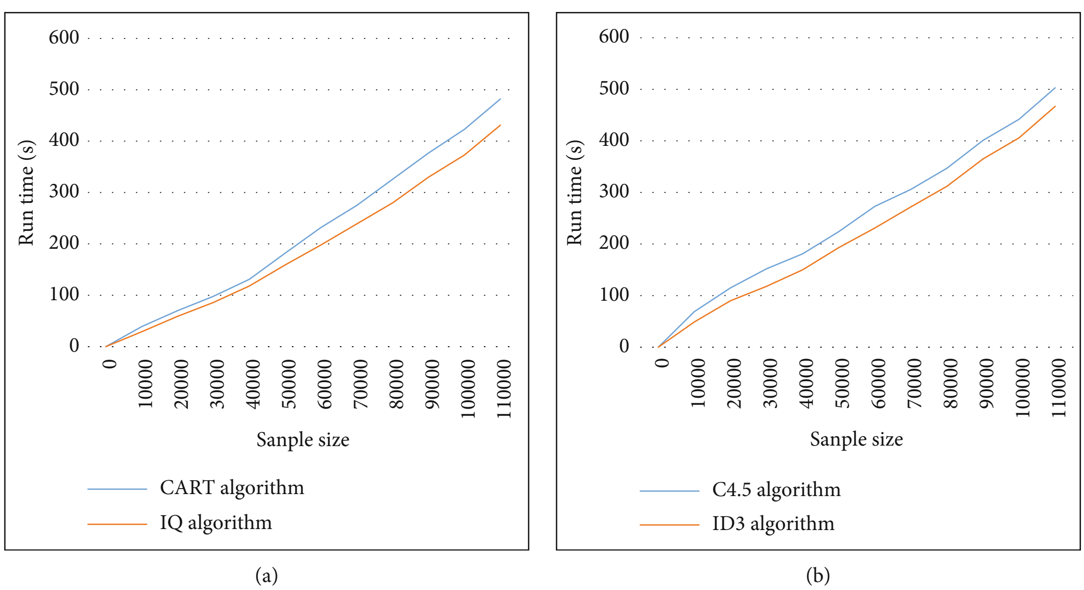

FIGURE 6: Comparison of running time of different algorithms under different samples. (a) Comparison of the running time of the CART algorithm and the IQ algorithm; (b) comparison of the running time of the ID3 algorithm and the C4.5 algorithm.

necessary to discretize the continuous values. Then,

$$m \leq \begin{cases} 2^r - 1 & r \geq 2 \\ 2 & r \angle 2 \end{cases} \tag{12}$$

where m indicates discrete classification numbers and r indicated the discrete continuous value.

$$p_k(x) = \frac{n_k(x)+1}{n(x)+1}, \tag{13}$$

$$q_k(x) = \frac{N_k(x)+1}{N(x)+1}, \tag{14}$$

$$S_p(x) = -[p_1(x)Inp_1(x) + p_2(x)Inp_2(x)], \tag{15}$$

$$S_q(x) = -[q_1(x)Inq_1(x) + q_2(x)Inq_2(x)], \tag{16}$$

$$p(x) = \frac{n(x)}{n}, \tag{17}$$

$$q(x) = 1 - p(x), \tag{18}$$

$$E(x) = p(x)S_p(x) + q(x)S_q(x), \tag{19}$$

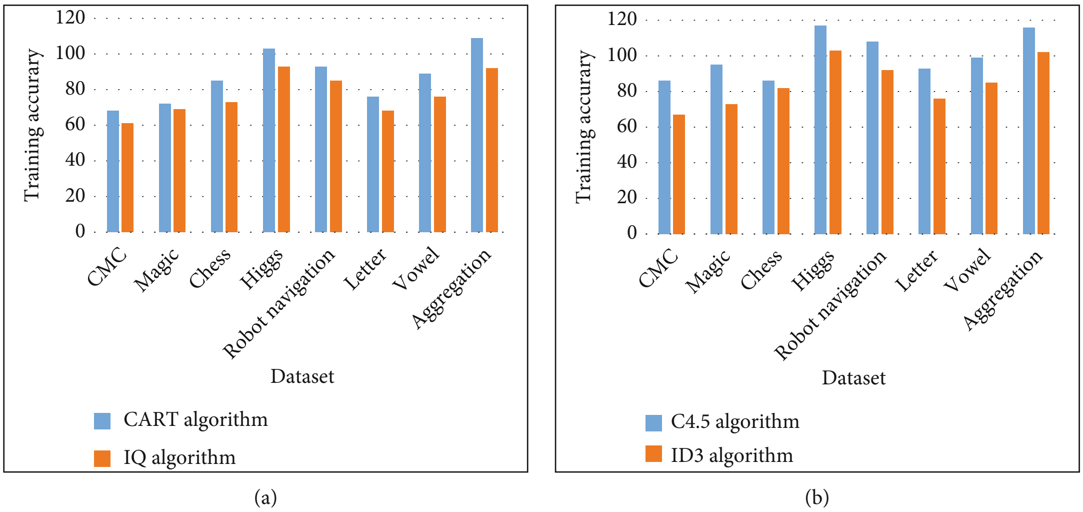

Figure 7: Comparison of training accuracy of different algorithms on eight datasets. (a) Comparison of training accuracy between CART algorithm and IQ algorithm; (b) comparison of training accuracy of ID3 algorithm and C4.5 algorithm.

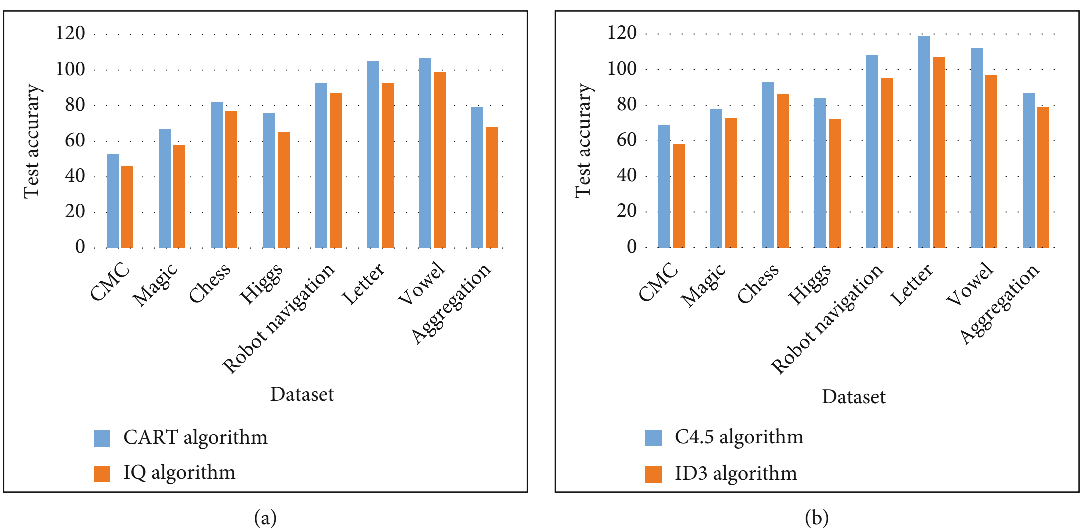

Figure 8: Comparison of test accuracy of different algorithms on eight datasets. (a) The comparison chart of the test accuracy of the CART algorithm and the IQ algorithm; (b) comparison of test accuracy of ID3 algorithm and C4.5 algorithm.

where p_1 indicates conditional attributes; S represents a collection of attribute p_1 values; p indicates the interval $[S_1, x]$ in which the set S is divided by x; q indicates the interval $[x, S_n]$ in which the set S is divided by x; and $E(x)$ represents the information entropy of x.

Discretize the continuous values of the set, then,

$$C = \begin{cases} L, & S_i \leq y_1, 1 \leq i \leq n \\ M, & y_1 \angle S_i \leq y_2, 1 \leq i \leq n \\ H, & S_i > y_2, 1 \leq i \leq n \end{cases} \quad y_1 = \frac{x_1' + x}{2}, y_2 = \frac{x_2' + x}{2}. \tag{20}$$

Among them, C represents the classification after discretization, and L, M, H represents the value of the classification value and represents "high," "medium," and "low" in turn.

(1) The process of CART algorithm is similar to C4.5 and ID3. The CART algorithm can only divide the sample data into two subsets, so the model of the tree is a binary tree. Since all the branches on the formed binary tree model are two, the CART algorithm can quickly generate a decision tree and make the decision tree more simplified [27].

(2) The three steps of the IQ algorithm are as follows: building nodes in the same category, pruning the decision tree, and segment building the decision tree model. The IQ algorithm uses attribute quartiles to repair decision trees. The decision tree model is obtained by judging the information gain rate [28].

3.4. Experiments and Analysis of Different Decision Tree Algorithms. This paper compares the four decision tree algorithms of ID3 algorithm, C4.5 algorithm, CART algorithm,

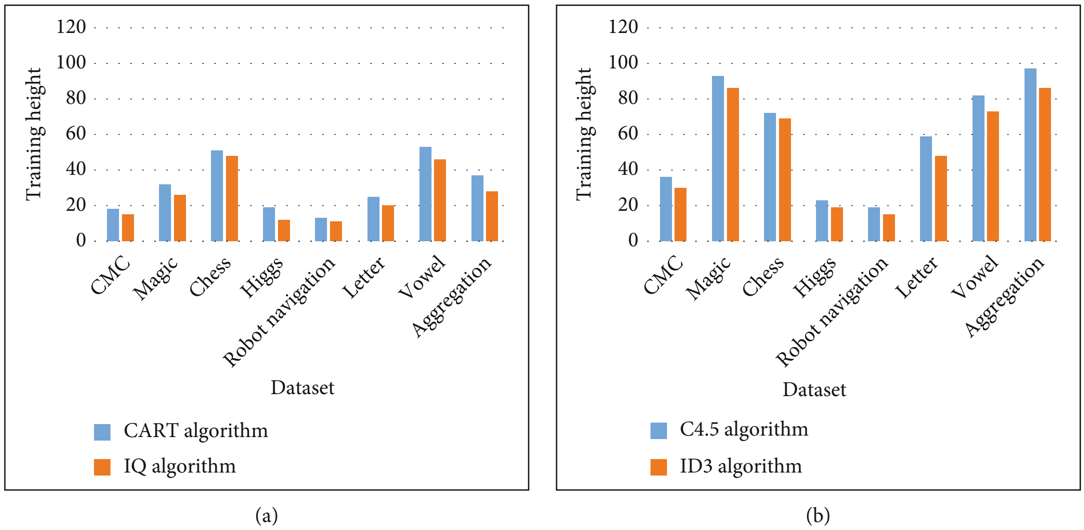

FIGURE 9: Comparison of tree heights for different algorithms on eight datasets. (a) The height comparison of the tree of the CART algorithm and the IQ algorithm; (b) comparison of tree heights for ID3 algorithm and C4.5 algorithm.

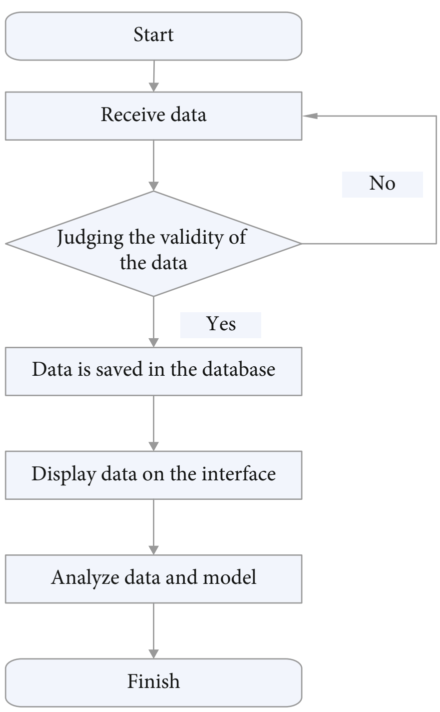

FIGURE 10: Flowchart of the global economic market forecast model.

and IQ algorithm through environmental tests. The first is the running time of the algorithm, the second is the classification accuracy of the decision tree model, and the third is the height of the tree that generates the decision tree model. The experimental data is the dataset in UCI, as shown in Table 2. The UCI dataset is a commonly used machine learning standard test dataset, and a total of 8 datasets are used.

3.4.1. Comparison of Running Time of ID3, C4.5, CART, and IQ Algorithms under Different Samples. This experiment uses the Letter dataset in UCI, as shown in Figure 6. Under the same parameters, the C4.5 algorithm runs faster and has higher execution efficiency.

3.4.2. Comparison of Training Accuracy of ID3 Algorithm, C4.5 Algorithm, CART Algorithm, and IQ Algorithm on Eight Datasets. As shown in Figure 7, the training accuracy of the ID3 algorithm and the C4.5 algorithm is compared. It is not difficult to see from Figure 7(b) that the C4.5 algorithm is significantly better than the ID3 and the training accuracy on the eight datasets does not drop significantly.

3.4.3. Comparison of the Test Accuracy of ID3,C4.5, CART, and IQ Algorithms on Eight Datasets. From Figure 8, it can be found that on the eight datasets, the test accuracy of the four algorithms does not drop significantly, and the C4.5 algorithm has the highest test accuracy.

(4) Comparison results of tree heights of ID3, C4.5, CART, and IQ algorithms on eight datasets

As can be expected from Figure 9, the heights of the decision tree model trees generated by the CART algorithm and the IQ algorithm are comparable. The ID3 algorithm is compared with the C4.5 algorithm; the height of the generated decision tree model tree is not high. Therefore, it can be found from Figure 9(b) that the C4.5 algorithm can generate a higher decision tree model tree or a lower decision tree model tree.

Through the analysis and comparison of the four main decision tree algorithms of machine learning, the C4.5 algorithm is selected for economic decision-making. C4.5 algorithm itself has the features of high sorting precision, fast sorting speed, and strong data processing ability. Therefore, the C4.5 algorithm has the characteristics of high classification accuracy and strong data processing ability to solve the difficult bottleneck problem in the global economic market. It overcomes the insufficiency of choosing attributes with many values when selecting attributes with information gain and can handle nondiscrete and incomplete data. The

Table 3: Global economic market data format table.

Category	Level	Instruction
National GDP	1	The sensor's data perception of the country
Currency devaluation	1	Sensor's data perception of currency
Stimulate economic policy	2	Sensors' data perception of policies
International trade	3	Sensors' data perception of trade
Institutional arrangements against global economic development	2	Sensor's data perception of the system

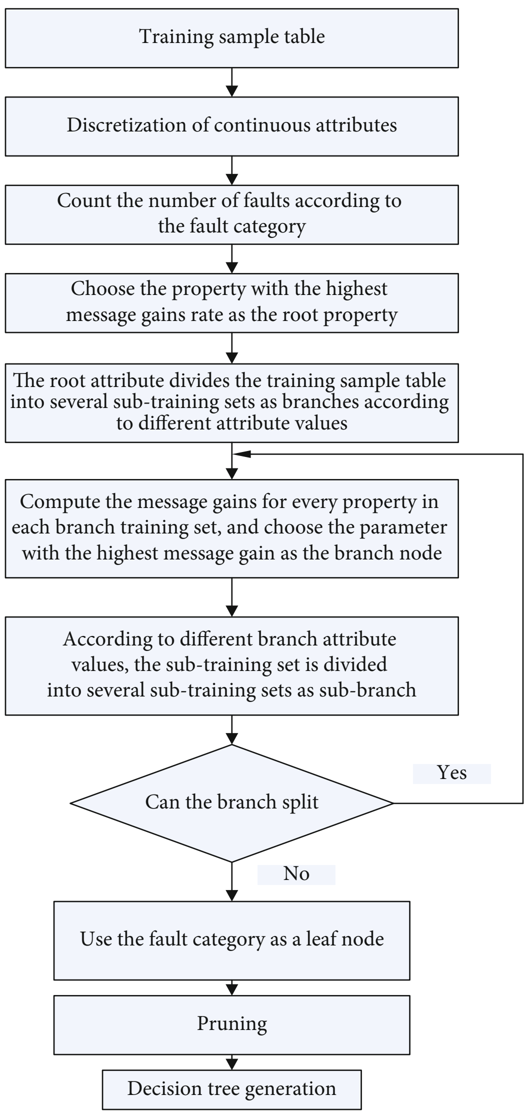

Figure 11: Decision tree generation process.

C4.5 algorithm can also use the characteristics of fast classification speed and easy-to-understand classification results to solve the problem of slow inference speed.

4. Global Economic Market Forecast Model and Decision-Making System

Global economic model forecasts start with receiving data. Go to the next step to identify whether the data is available. If the data is wrong or incomplete, it will be discarded and wait for the next data. After re-receiving new data, if available, it will be stored in the local database and displayed in the software interface. Finally, it is processed by the global economic market decision-making module, and data modeling and analysis are performed as shown in Figure 10.

Create a global economic market decision tree model with the data of the economic market as a sample. And use the model to analyze the probability of the US economic downturn, emergency policies for the next economic recession, the degree of influence of the financial market, the evolution of global trade frictions, and the development trend of de-globalization to make global economic market decisions.

In 2020, the world economy shows that the economies of many countries have begun to decline, and only a few countries such as the United States are still experiencing strong economic growth rates. As a world power, the United States has a serious impact on the world economy. If the US economy continues to grow, it may lead the global economy into the next boom. But if the US economy continues to decline, it is very likely that the world will enter a new round of economic crisis. So, in 2021, a large part of the reason for the direction of the world economy depends on the direction of the US economy.

The current national currency crisis is one of the main factors that trigger the financial crisis, especially that the currency devaluation of emerging market countries is a wake-up call for the financial crisis. Also, as we all know, the debt of various countries is also a high-risk factor that triggers a financial crisis. When a country has a large debt to bear, it will be easy to fail to repay on time or to default directly, thus causing global economic chaos. The rapid recession or decline of the real economy in the United States will also affect other countries; many countries in the world are highly dependent on the US market. Once the US economy declines and demand declines, it will directly affect the export earnings of many countries, which will affect the economic downturn of many countries and slow down the global economic growth rate, and these three types of factors are likely to occur. If it happens in one category, it will also affect other countries, causing global economic turmoil. If the three types occur together, it will cause harm to more countries and cause significant losses to the world economy.

If there is a global economic crisis in the near future, it will be difficult for countries, especially developed countries, to deal with it. In recent years, it has been shown that the economic growth policies of developed countries are not very effective. This problem is reflected in the country's overall economic coordination policy and monetary and financial policies.

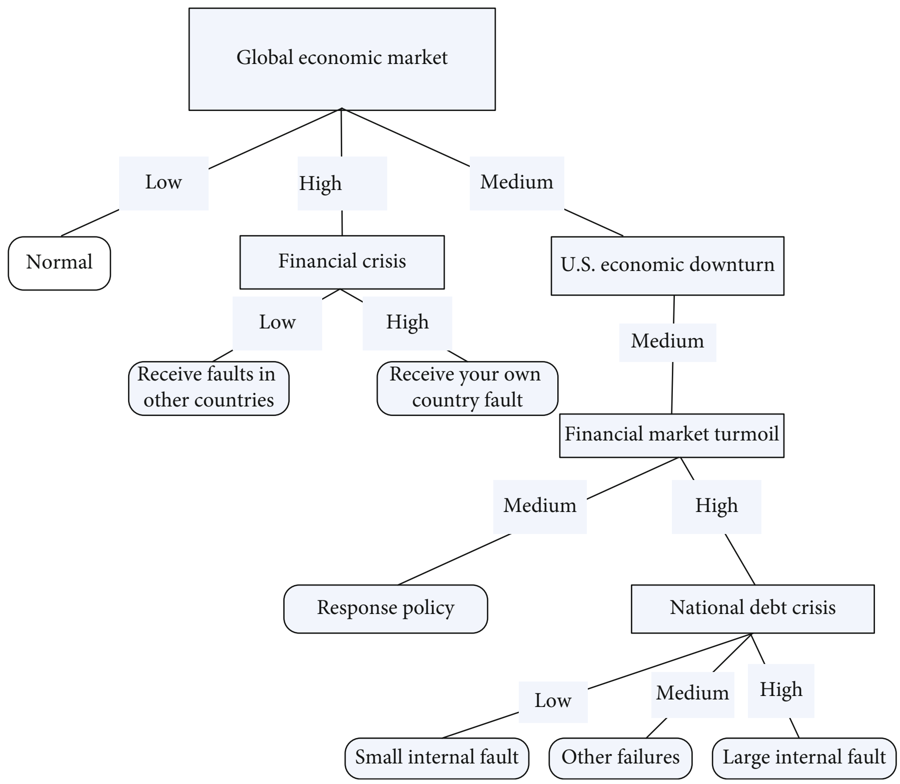

Figure 12: Schematic diagram of the decision tree of the global economic market.

Trade friction is a chain reaction. Some countries have begun to implement policies that affect international trade, such as increasing tariffs. This will not only affect the economy of their own country, but also the economy of the other country. In these years, China's trade has begun to show a downward trend. Trade frictions have had a big impact; if country A's exports of agricultural products decrease, the other countries will increase accordingly. This will cause an imbalance in the international division of labor, disrupt the safe business environment that the World Trade Organization has painstakingly created, and cause a drop in global productivity. In the long run, this will have a very bad impact on the world economy. The implementation of a country's system not only has a profound impact on its own country, but if it is a system that reverses global economic growth, the economy of other countries will also be affected for a long time.

The historical data collected through the wireless sensor network is preprocessed to define the data format according to the decision tree C4.5 algorithm, as shown in Table 3.

According to the preprocessed historical data of the global economic market, the decision tree C4.5 algorithm is used to model the decision tree. The specific process of generating a decision tree is shown in Figure 11.

The data format table is used as a training sample, and the decision tree C4.5 algorithm is used to calculate after discretization. And use the postpruning method to prune the generated original decision tree to generate the final decision tree. The generated global economic market decision tree is shown in Figure 12.

5. Discussion

With the progress and growth of industry and society, many learning frameworks on IoT have been established and applied in various areas in these years, for example, industry and real-time forecasting. Machine learning achieves prediction and judgment on the future by designing some computers to analyze data, obtain the characteristics of things, and find the rules. Decision tree algorithm is the most widely used algorithm in machine learning. Through the comparison of experimental data of different decision tree algorithms, the following conclusions can be drawn:

(1) The advantages and disadvantages of different decision tree algorithms. Through the comparative analysis of related concepts of different decision tree algorithms, the C4.5 algorithm is more in line with the global economic market forecast and decision-making system

(2) The time the algorithm runs. The operating efficiency of the four algorithms, ID3, C4.5, CART, and IQ, increases with the increase of the dataset. When the dataset increased to 110,000, the operating efficiency continued to increase

(3) Classification accuracy of decision tree models. Through the experimental analysis of the training precision and test precision on the eight datasets, the accuracy of the four algorithms does not decrease or increase significantly, and the C4.5 algorithm has the highest accuracy

(4) Generates the height of the decision tree model tree. It can be seen from the experimental data that the heights of the decision tree models of the four decision tree algorithms do not fluctuate significantly on the eight datasets. It shows that the four decision tree algorithms are fast in calculation and relatively stable

The whole comparative test data shows that the C4.5 algorithm is superior to other decision tree algorithms in terms of the running time of the algorithm, the classification accuracy of the decision tree model, and the height of the generated decision tree model. This verifies the feasibility of the C4.5 algorithm in terms of execution efficiency.

6. Conclusion

With the acceleration of economic globalization and the increasing integration of national economies into the global competitive environment, how to use various technologies to better predict the data of the global economic market and make accurate decisions is a problem that needs to be considered under the current global economic integration. This paper introduces the decision tree algorithm of the IoT technology and machine learning and analyzes and compares the main decision tree algorithms of machine learning. Combined with the situation of the global economic market, it selects the C4.5 algorithm to complete the data processing of the global economic market information. At the same time, it combines the global economic market forecasting model and the decision tree C4.5 algorithm to form a global economic market decision-making system based on the IoT and machine learning. The article explores the optimal decision tree algorithm through comparative experiments of four decision tree algorithms: ID3 algorithm, C4.5 algorithm, CART algorithm, and IQ algorithm. The experimental results show that the C4.5 algorithm has the best execution efficiency when the test accuracy, training accuracy, and tree height range of the decision tree are relatively small. The accuracy and classification speed of C4.5 are more in line with the actual situation of the global economic market forecasting and decision-making system. Thereby, it promotes the progress of the related work of global economic market forecasting and decision-making and has a very good application value. The global economic market forecasting and decision-making system is very complex and covers a wide range of areas. Due to my limited time, energy, and resource constraints, there are some shortcomings in this paper, such as the refinement and expansion of the global economic market forecast model.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that they have no competing interests.

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