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Design of Intelligent Logistics Management System Based on Machine Learning

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Abstract. In today's business environment, intelligent logistics management systems have become a key pillar in multiple industries, especially in industries such as construction and machinery. Computer-aided design (CAD) technology has proven its enormous potential in design support. In the vast field of logistics, CAD technology has shown remarkable potential in terms of precision and efficiency. In order to further enhance the intelligence level of logistics management, this article proposes a new design concept - combining CAD and machine learning technology to build an intelligent logistics management system. By using CAD technology, we can accurately plan logistics paths and optimize warehouse layout, thereby significantly improving the efficiency of goods transportation. This not only saves costs for enterprises but also improves overall operational efficiency, injecting new vitality into the development of the logistics industry. The core of this system lies in using CAD technology to construct accurate models of logistics scenes and analyzing and predicting massive logistics data through machine learning algorithms to achieve automation and intelligence in logistics management. Experimental data shows that compared with traditional support vector machine (SVM) algorithms, FSVM reduces the error rate by 32.17% and improves accuracy by 13.47% when processing different transaction sets. This result fully demonstrates the superiority of the FSVM algorithm in logistics data processing.

Keywords: Logistics Management System; CAD; Machine Learning; Teaching Application
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1 INTRODUCTION

Intelligence, automation, and efficiency have become new directions for logistics development, while traditional logistics management methods have become inadequate in the face of modern and complex logistics needs. Thanks to the rapid development of CAD technology and machine learning algorithms, we now have strong technical support to design and implement intelligent logistics management systems. The core of this article is to explore the design concept of an intelligent logistics management system that integrates CAD and machine learning and analyze the application value of the system in logistics education. Industry 4.0 is a cutting-edge and eye-catching concept that focuses on the automation, digitization, and seamless exchange of industrial data for systems and processes. Especially in the field of supply chain management, the application of Industry 4.0 is still in its early stages, but its potential and importance have gradually become apparent. The application of this concept has undoubtedly brought revolutionary changes to multiple fields such as manufacturing, supply chain, and logistics. In view of this, Abdirad and Krishnan [1] conducted a systematic review and synthesis of existing literature on Industry 4.0 in supply chain management, in order to uncover the profound insights and inspirations contained therein. According to the different characteristics of the paper content, it is divided into three categories: exploratory and confirmatory, qualitative and quantitative, and management level and process/technical level. Its core goal is to achieve an intelligent factory that significantly shortens the delivery cycle in response to customer needs or unexpected events, and significantly improves the efficiency of the entire production system. For a long time, we have faced the challenge of insufficient flexibility and adaptability in process control. The rigid mode makes it difficult for machine operators to effectively utilize the large amount of process knowledge accumulated in their daily work, and cannot contribute to the optimization and improvement of process control. To overcome this dilemma, Bricher and Müller [2] proposed a novel container logistics fully automated process control solution based on deep neural networks. By leveraging the powerful learning capabilities of deep neural networks, the wisdom behind these decisions can be transformed into reusable control strategies. They fully utilized the inherent characteristics of the logistics process and designed a fully automated framework to label container images. This innovation not only greatly reduces the workload of operators but also eliminates the tedious process of manual marking. Not only can it effectively solve the problem of insufficient flexibility and adaptability in manufacturing process control, but it can also fully utilize the process knowledge of employees to achieve continuous optimization and improvement of process control. In some extreme cases, this chain even extends to the final stage of commodity production. This is not just a simple software model but also a brand-new, cross-functional system architecture. To address this challenge, Capua et al. [3] proposed a novel solution - the Integrated Logistics Platform (ILP 4.0). It goes beyond traditional fragmented management and follow-up methods, aiming to achieve strategic coordination of all logistics activities and lead warehouse logistics to a new level of efficiency. This not only highlights the importance of managing the post-production stages of products and commodities but also reveals the complexity and pressure faced by the personnel managing these activities. By integrating machine learning and computer vision methods, as well as augmented reality (AR) and virtual reality (VR) devices, they attempted to build an "intelligent" warehouse model environment. This environment not only automates the inventory process (such as automated inventory management through drones) but also accurately controls the movement within the warehouse, ensuring the logical and physical security of the premises.

As an emerging technology, blockchain technology is still in its early stages of application in the fields of transportation and logistics. Although the application of Internet-based technology has brought efficiency and convenience to the logistics industry, it has also brought more potential security risks to the logistics environment. To address this challenge, Cheung et al. [4] reviewed the current research status of strengthening network security measures in logistics and supply chain management. Through an in-depth analysis of these studies, they discovered some key findings and revealed possible future research directions. Secondly, although logistics plays a crucial role in the supply chain, there is not much research specifically focused on logistics network security. Once these security risks are transformed into actual attacks, they will have a serious negative impact on the performance of logistics processes and even the entire supply chain. Ding et al. [5] systematically summarized the latest research and application achievements of intelligent logistics based on the Internet of Things. They found that Internet of Things technology is increasingly becoming an important support in the field of intelligent logistics. It can not only achieve real-time monitoring and intelligent scheduling of logistics processes but also provide more accurate decision support for logistics enterprises through big data analysis and prediction. Through bibliometric analysis of a large number of publications from 2008 to 2019, they revealed the current research and application status of intelligent logistics based on the Internet of Things, as well as its main technologies and impacts in different industries and geographical distributions.

The rise of intelligent logistics has also brought about a profound transformation in the narrative of logistics management. In this context, intelligent logistics has emerged as an efficient solution to address the increasingly complex and massive logistics demands. The application of these technologies has greatly improved the efficiency and accuracy of logistics operations, enabling precise control and efficient coordination of every link from production to consumption of goods. Under the wave of globalization, the collaboration and integration of online and offline channels have brought unprecedented challenges and opportunities to the logistics industry. The flourishing development of cutting-edge technologies such as the Internet of Things, information and communication technology, and artificial intelligence has provided strong technical support for the intelligence of the logistics industry, making logistics operations more efficient and accurate. However, this technological revolution not only improved logistics efficiency but also profoundly changed the narrative of logistics management. The traditional logistics model is no longer able to meet the growing business needs, and intelligent logistics has emerged as a good solution to cope with the complex and ever-changing logistics environment. Research on the operation and management of intelligent logistics is no longer limited to the application of underlying technologies; it also focuses on optimizing business logic, constructing operational frameworks, innovating related management systems, and optimizing problems in specific scenarios. Through the analysis of existing research, we have found that although intelligent logistics has made significant progress, there are still many research gaps and challenges in industrial practice [6]. Blockchain technology and the Internet of Things have gradually become key driving forces for the transformation and upgrading of modern supply chains. The digital reverse supply chain that combines these two provides unprecedented opportunities and challenges for enterprises. Hrouga et al. [7] explored the potential of blockchain technology and the Internet of Things in digital reverse supply chains through case studies. The reverse supply chain focuses on the recycling, reuse, and disposal of products to achieve effective resource circulation and sustainable environmental development. A digital reverse supply chain utilizes digital technology to optimize this process and improve efficiency and transparency. Through this example, they found that the satisfaction rate of multi-objective optimization reached 0.92, which is much higher than the satisfaction rate of single-objective optimization. It constructs a multi-objective closed-loop logistics network model for fresh produce under uncertain conditions. The comparison results show that the improved GA has higher optimization performance and stability in solving multi-objective complex constraint problems, further highlighting its superiority.

Logistics, as an important pillar of the modern economy, its operational efficiency is directly related to the competitive strength of enterprises and the stability of the market. However, due to limitations in manpower and traditional experience, traditional logistics management models face difficulties in achieving precise and efficient logistics operations. CAD technology, as a powerful auxiliary design tool widely used in fields such as construction and machinery, also shows infinite possibilities in the logistics field. CAD can not only help us accurately plan logistics paths, optimize warehouse layout, and improve cargo transportation efficiency [8], but it can also be used to simulate and analyze the operation of logistics systems and timely identify and optimize potential problems. In addition, the excellent capabilities of machine learning algorithms in data processing and predictive analysis have also brought new opportunities for logistics management. By applying machine learning, historical logistics data can be deeply excavated, revealing hidden patterns and trends and providing data support for logistics decision-making.

The intelligent logistics management system, combining the accuracy of CAD technology and the data insight of machine learning algorithms, not only significantly improves the efficiency of the logistics industry but also brings revolutionary teaching methods to the field of logistics education. Through the introduction of this system, students majoring in logistics can have a more intuitive understanding of the practical operations of modern logistics management. The following are the core innovations of this study.

This study proposes for the first time a design concept for an intelligent logistics management system that combines the accuracy of CAD technology with the data insight ability of machine learning. This innovative fusion method provides an unprecedented intelligent solution for logistics management.

In addition to the traditional application of CAD in path planning and warehouse layout, this study further explores its potential in logistics system simulation and operational analysis to anticipate and solve potential problems.

In order to handle complex logistics data, including uncertainty, noise, and outliers, this study innovatively introduces the FSVM algorithm, which significantly improves the accuracy of data processing and prediction, opening up new avenues for logistics data analysis.

2 RELATED WORK

In today's digital wave sweeping the world, Liu et al. [9] proposed a new business model - cloud laundry services based on Internet of Things (IoT) technology, which aims to provide unprecedented convenience and efficiency for large-scale laundry services. Due to its intelligent operation mode and efficient logistics management system, cloud laundry companies can quickly respond to market demand, reduce operating costs, and improve profitability. With the help of Internet of Things technology, cloud laundry can obtain and update real-time status information of laundry terminals, including device usage, washing progress, etc. This intelligent solution not only improves the efficiency of laundry services but also brings users a more convenient and efficient experience. Mohanta et al. [10] delved into various factors that may affect the severity of vehicle accidents in order to provide a more scientific and accurate basis for accident prevention and emergency response. This not only proves the applicability of these models in intelligent transportation systems but also provides valuable experience for our subsequent research. These models each have their own characteristics; some are good at handling linear relationships, while others are good at capturing nonlinear features. Some are suitable for processing large amounts of data, while others perform excellently on small datasets.

Industrial logistics is not just about the simple transportation of goods but also involves the complex and meticulous task of identifying processing processes from CAD models provided by customers and finding suitable manufacturing suppliers based on them. Peddireddy et al. [11] proposed a novel MPI system based on three-dimensional convolutional neural networks (CNN) and transfer learning, which aims to free up manpower and improve recognition accuracy and efficiency. Those functions that are closely related to analyzing materials and information flow enable us to conduct in-depth analyses and simulations of every link in the logistics process, thereby identifying potential problems and proposing targeted improvement plans. As an important tool in this field, modelling software provides powerful support for designing and evaluating complex logistics systems through continuous upgrades and improvements in their functionality. The introduction of this technology not only provides us with a new perspective and method to examine and optimize the logistics process but also plays an irreplaceable role in improving logistics efficiency and reducing operating costs. Through the CET table system, we can accurately model the logistics process, simulate various possible scenarios and situations, and provide more comprehensive and accurate data support for enterprise decision-makers [12]. In the initial design, blockchain was mainly used to support financial transactions, bringing significant benefits to the financial industry by eliminating intermediaries, reducing transaction costs, and improving transaction speed. For a long time, various aspects of the manufacturing industry have relied on close relationships and mutual trust with upstream and downstream stakeholders to ensure smooth operations. Through blockchain technology, supply chain and logistics operations can become more secure, agile, trustworthy, and transparent. It can also optimize inventory management and logistics distribution and improve the response speed and flexibility of the supply chain. In addition, blockchain can also help enterprises reduce operating costs, improve operational efficiency, and enhance trust and cooperation with partners [13].

The Internet of Things is like an invisible pair of eyes that can penetrate every corner of the supply chain, observing, tracking, and monitoring products, activities, and processes. Through IoT technology, enterprises can achieve real-time monitoring and prediction of warehouse inventory, optimize production line layout and processes, and improve transportation efficiency and safety [14]. As a technology that can achieve data immutability, sharing, and transparency, it makes the flow of information in the supply chain more efficient and accurate. Through blockchain technology, Treiblmaier [15] has established a supply chain system based on shared data views, enabling all parties to obtain the required information in real-time and accurately, thereby improving the transparency and traceability of the supply chain.

3 BUILDING AN INTELLIGENT LOGISTICS MANAGEMENT PLATFORM

The intelligent logistics management platform is an indispensable part of the modern logistics system, which integrates cutting-edge information technology and management strategies, aiming to promote the intelligence, automation, and efficiency of logistics processes. This section will elaborate on the construction process of this platform, covering requirement analysis, architecture construction, and logistics optimization strategies using CAD technology.

3.1 Demand Insights

At the beginning of building an intelligent logistics management platform, we need to have a comprehensive insight into the needs that the platform needs to meet. This process not only focuses on the functional requirements that the platform should have but also involves non-functional expectations, as detailed in Table 1.

Functional requirements	*Non-functional requirements*
Data capture and input, information processing and analysis, intelligent decision-making assistance, information dissemination and sharing, system security and permission control	Efficiency expectations, usability requirements, flexible scalability requirements, and robust maintenance requirements

Table 1: System requirements.

Core functional requirements refer to the key tasks that the system must perform and the functions provided. In the context of intelligent logistics management systems, their core functional requirements cover the following points:

Information capture and integration: The system needs to be able to capture and integrate diverse logistics information in real-time, such as order details, storage status, and cargo transportation status.

Data Analysis and Insight: The system needs to have excellent data analysis and deep mining capabilities, which can clean, classify, deeply analyze, and visually present the collected data in order to extract valuable business insights.

Intelligent decision assistance: Based on the parsed data, the system should be able to provide logistics management personnel with intelligent decision assistance in path selection, inventory control, and order allocation.

3.2 System Framework Construction

After fully understanding and determining the various requirements of the system, the next key step is to build a stable and efficient system framework to meet and implement these requirements. For the comprehensive framework design of intelligent logistics management systems, modular design thinking should be followed to ensure the expansion space of the system and attach importance to its subsequent maintenance convenience. This design concept is detailed in Table 2.

Architecture hierarchy	*Core Responsibilities*	*Technical Core*
Data storage and management module	Undertake data storage, disaster recovery, and recovery tasks	Build an optimized database architecture to ensure the security, integrity, and coherence of data
Core logic processing module	Practice the business logic of the centre, covering data processing and strategy assistance.	Introduce advanced machine learning algorithms, conduct in-depth analysis of data, and provide flexible and scalable business logic access ports.
User interaction display module	The present user interface visually displays information and accepts user instructions.	Emphasize the importance of user experience and apply responsive design techniques to ensure high-quality interactive experiences on various devices.
System interconnection module	Realize data exchange and information transmission with other systems	Establish a unified data interface specification to achieve smooth communication and shared utilization of information

Table 2: System framework construction.

User interaction display module: This module focuses on creating an intuitive and user-friendly user interface and providing users with a convenient interactive experience so that they can easily view and operate information.

System interconnection module: Its responsibility is to establish a connection bridge with other systems, ensure seamless data transmission, and achieve information sharing and collaborative operations.

Based on the overall architecture blueprint, core components can be further conceptualized to meet specific functional requirements. The following are preliminary ideas for several core components:

Information capture component: Utilize API ports, sensors, or diverse information sources to instantly capture logistics dynamics and then save this data to a data warehouse.

Data Processing and Insight Component: Screening, sorting, deep exploration, and visualization of captured data, aiming to extract valuable information and insights.

Smart strategy assistance component: Based on processed data, it provides users with intelligent decision-making assistance such as path selection, inventory reserves, and order allocation.

Information transmission and collaboration component: Real-time push of processed information and decision results to relevant personnel while supporting information sharing and team collaboration.

Security protection and permission control components fully guarantee the security of the system and user privacy, effectively preventing any unauthorized access and operation behavior.

3.3 Utilizing CAD Technology to Improve Logistics Management

With the powerful functions of CAD technology, more detailed planning and control of logistics processes can be achieved. Table 3 provides a detailed overview of this process.

Optimization method	*Detailed content*	*Technical practice*
Improvement of delivery routes	Taking into account road traffic conditions, carefully select the most efficient delivery route	Construct visual charts of distribution networks through CAD programs and then use the shortest path algorithm to finely optimize distribution routes
Optimize storage space configuration	Scientific layout of storage space, completing material handling with the shortest distance and shortest time	Using CAD tools to conduct simulation experiments on the spatial configuration of the warehouse, continuously adjusting to achieve maximum efficiency
System simulation and prediction	By simulating the operation of logistics systems, pre-evaluate the potential effectiveness of various strategies	Integrating CAD design and simulation technology to comprehensively simulate logistics processes and evaluate their performance

Table 3: Logistics optimization methods.

(1) Delivery route improvement: With the help of CAD technology, taking into account various factors such as road conditions and traffic flow, carefully design logistics delivery routes to select the most efficient delivery route.

(2) Optimize warehouse space configuration: Using CAD technology, scientifically plan the internal space of the warehouse, aiming to shorten the transportation path of goods, reduce processing time, and thus improve the overall operational efficiency of the warehouse.

(3) System simulation and prediction: Through CAD technology, the logistics system is simulated and predicted to comprehensively evaluate and analyze the effectiveness and performance of various strategic solutions.

4 THE APPLICATION OF THE FSVM ALGORITHM IN THE FIELD OF INTELLIGENT LOGISTICS

The FSVM algorithm, as an advanced version of SVM, incorporates the concept of fuzzy mathematics. This innovation makes the algorithm perform better in handling ambiguous, noisy, or abnormal data. In the complex field of intelligent logistics, the diversity and complexity of data make the application of the FSVM algorithm crucial. Please refer to Figure 1 for relevant illustrations.

The FSVM algorithm is an innovative extension of the traditional SVM algorithm, which specifically adds a fuzzy factor to handle uncertainty in data. In the standard SVM algorithm, each data point is given the same weight equally; However, in the FSVM algorithm, each data point is assigned a fuzzy membership value. This specific numerical value represents the degree to which data points belong to a certain category. By introducing the concept of fuzzy membership degree, FSVM exhibits higher efficiency in processing data points close to the classification boundary, thereby improving the accuracy of classification.

Set as an element that affects the prediction of logistics traffic flow and represents the predicted logistics traffic flow value. Building a real-time logistics data processing and prediction model based on FSVM, with the core goal of exploring the inherent relationship between and.

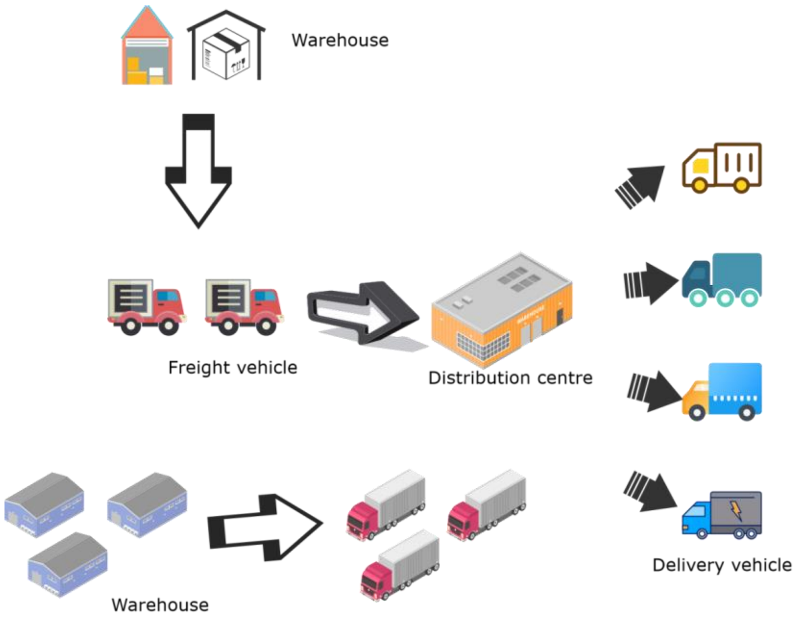

Figure 1: Improvement of the logistics transportation path.

$$f : R^n \rightarrow R \tag{1}$$

$$y_i = f\left(x_i\right) \tag{2}$$

R^n plays a core role in real-time data processing and logistics prediction. Building a traffic flow prediction model:

$$f\left(x\right) = \sum_{i=1}^{k}\left(a_i - a_i^*\right)K\left(x, x_i\right) + b \tag{3}$$

This scenario is defined as various elements of left and right logistics traffic flow while x_i representing i representative samples selected from k samples. In addition, $K\left(x, x_i\right)$ is used to refer to the kernel function, and the kernel function we have chosen is in the following radial basis function form:

$$K\left(x, y\right) = \exp\left(-\frac{\left\|x-y\right\|^2}{2\sigma^2}\right) \tag{4}$$

Intelligent logistics management requires in-depth analysis and accurate prediction of massive data, which includes multiple aspects such as order volume prediction, inventory management strategy formulation, and transportation path optimization. However, these data are often influenced by multiple factors such as changes in market demand, supply chain stability, weather conditions, etc., so there will inevitably be some uncertainty and noise interference in the data. The FSVM algorithm cleverly introduces the concept of fuzzy membership, enabling it to efficiently cope with these uncertainties and noise, thereby demonstrating higher accuracy in prediction and classification tasks.

The optimal classification surface not only satisfies the requirement of accurately separating the two types of training samples but also further pursues the maximization of the classification interval to achieve the best classification effect. For a schematic diagram of the optimal hyperplane, please refer to Figure 2.

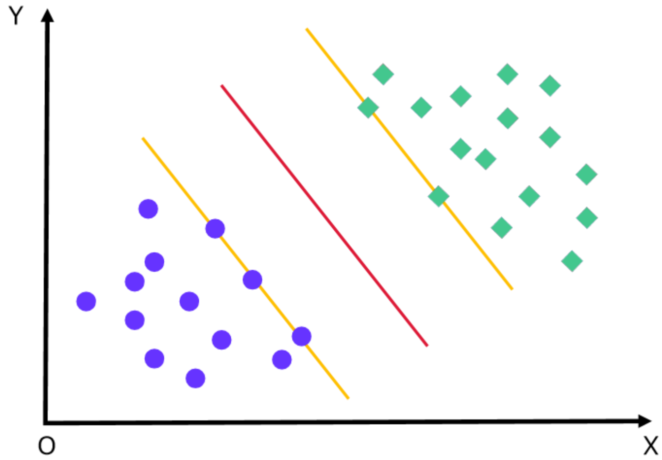

Figure 2: Optimal hyperplane.

The cost of vehicle transportation is closely related to the distance travelled, which is manifested as a positive proportional relationship:

$$C_1 = \sum_{i \in N} \sum_{j \in N} \sum_{k \in K} tcost_k * x_{ijk} * d_{ij} \tag{5}$$

The transportation cost will increase correspondingly with the extension of driving distance.

In this scenario, $tcost_k$ is used to represent the transportation cost per unit of a specific vehicle k, while d_{ij} is used to represent the geographical distance between customer i and customer j. $tcost_k, d_{ij}$ is a preset fixed value. In addition, we introduced the 0-1 variable x_{ijk}, which is used to mark whether the vehicle k is moving from location i to location j. If such movement does occur, then the value of x_{ijk} is 1; On the contrary, if there is no such movement, the value of x_{ijk} will be 0.

Set an acceptable waiting time range for customers, which is the highest and lowest time limits. Meanwhile, construct a function to link the waiting time with the compensation that the customer deserves. Once the customer's waiting time exceeds the preset minimum time limit, the system will automatically calculate and impose fines. The calculation of penalty costs follows the following standardized formula:

$$K \ t_{ij} = \begin{cases} 0, & t_{ik} < a \\ M \ j \ \ t_{ik} - a \ , & t_{ik} > a \end{cases} \tag{6}$$

In this case, $K \ t_{ij}$ represents the penalty cost for time window violations related to the vehicle i serving the customer j. $M \ j$ refers to the additional cost that needs to be borne for each additional unit of delay beyond the time limit set by the customer j. t_{ik} is used to record the specific time when the car k arrives at the customer i.

The FSVM algorithm not only demonstrates excellent generalization ability but also effectively handles high-dimensional data and nonlinear problems. In the field of intelligent logistics, data usually has high-dimensional and non-linear characteristics, such as order data containing multiple dimensions such as product types, quantities, prices, etc., and transportation path planning is also affected by various complex factors such as road conditions and traffic congestion. When using the FSVM algorithm, it is necessary to first determine the calculation method of fuzzy membership degree, then select a suitable kernel function to handle the nonlinear features of the data, and finally make detailed parameter adjustments to the model to ensure its performance reaches the best. For the FSVM-based traffic data classification method, you can refer to Figure 3 for a more intuitive understanding.

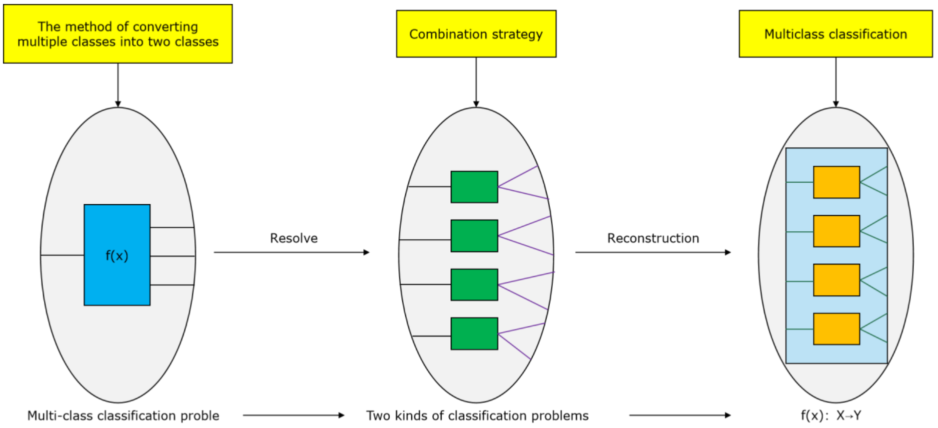

Figure 3: Classification of traffic data.

This article elaborates on a logistics data processing method based on FSVM, which can accurately classify data in unclassified areas based on the distance between data points and classification hyperplanes. According to the operation process of the FSVM algorithm, the optimal classification surface function can be expressed as $f_{ij}\ x$:

$$f_{ij}\ x\ = \operatorname{sgn}\left(\sum_{i=1}^{N} \alpha_i y_i K\ x_i, x_j\ + b\right) \tag{7}$$

The constituent element of x is x_i, with the latter serving as its key input; α_i plays the role of Lagrange multiplier here; b is used to set the critical value for classification; y_i is responsible for indicating the category labels of the output; $K\ \cdot$ is a specific kernel function used for data processing.

The linear regression function in high-dimensional space can be expressed as:

$$f\ x\ = \omega \cdot x + b \tag{8}$$

The ε linear insensitive loss function is now defined as follows:

$$e\ f\ x\ - y\ = \begin{cases} 0, & \left|f\ x\ - y\right| < \varepsilon \\ \left|f\ x\ - y\right| - \varepsilon, & \left|f\ x\ - y\right| \geq \varepsilon \end{cases} \tag{9}$$

In predictive analysis, $f\ x$ represents the predicted result of the regression function, while $f\ x\ , y$ is the corresponding actual value. When the difference between the predicted value and the true value does not exceed ε, we call this prediction a perfect match, and the loss is zero.

The final output of the FSVM algorithm is:

$$\begin{cases} \omega = \sum_{i=1}^{l} \alpha_i - \alpha_i^* \ \phi \ x_i \\ f \ x \ = \sum_{i=1}^{l} \alpha_i - \alpha_i^* \ k \ x_i, x \ + b \end{cases} \tag{10}$$

The kernel function is defined as:

$$k \ x, x' \ = \left\langle \phi \ x \ , \phi \ x' \ \right\rangle \tag{11}$$

Any symmetric function that satisfies the Mercer condition can be called a kernel function.

With the introduction of fuzzy membership values, the FSVM algorithm can effectively deal with the uncertainty and noise interference in the data. Meanwhile, by selecting appropriate kernel functions and fine parameter tuning strategies, the FSVM algorithm can further enhance its decision-support ability in the field of intelligent logistics management, providing managers with a more robust and reliable decision-making basis.

5 RESULT ANALYSIS AND DISCUSSION

5.1 Experimental Environment

In order to test the practicality of the intelligent logistics management system that integrates CAD and FSVM in teaching, a dedicated experimental environment was specially constructed for empirical research (specific configurations are shown in Table 4).

Configuration items	*Version/Model*
operating system	Windows 10
development environment	Python 3.8, MATLAB R2022a, Visual Studio Code
database	MySQL 8.0
processor	Intel Core i7-9700K
Memory	32GB DDR4 3200MHz
storage device	1TB NVMe SSD
Graphics card	NVIDIA GeForce RTX 2070
processor	Intel Core i7-9700K

Table 4: Software and hardware configuration.

To ensure the uniformity and reproducibility of the experiment, strict control was implemented over the software versions used throughout the entire experiment to ensure consistency throughout the entire process. At the same time, thorough testing was conducted on the hardware system to confirm its stability, reliability, and performance standards, which can meet the various requirements of the experiment. In addition, to prevent data loss, regular data backups were conducted during the experimental process.

5.2 Experimental Result

In the field of logistics management, significant differences in data distribution intervals are a common problem, which can be attributed to multiple factors such as region, time cycle, and product type. When the distribution intervals of data differ significantly, directly processing and analyzing these data will face challenges, as the impact of data from different intervals on the results may be imbalanced. To address this issue, inter-region dispersion processing of data has become a practical solution.

The so-called interval discretization processing refers to dividing the originally continuous data range into several independent discrete intervals, each corresponding to a specific data range. The advantage of this method is that it can reduce the complexity of data analysis and make the data easier to understand and interpret. In response to the significant differences in interval distribution in logistics data, we adopted the method of interval discretization. The specific processing method is shown in Figure 4.

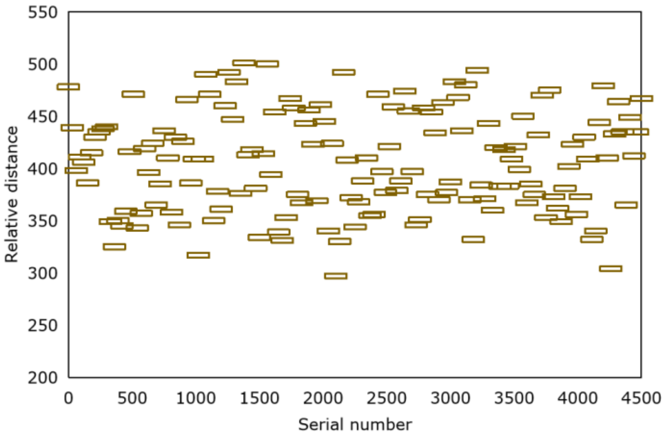

Figure 4: Data removal of outliers.

With the help of inter-regional dispersion processing technology, logistics data that was originally scattered and had significant interval differences can become more standardized, making it easier to conduct in-depth data analysis. When planning logistics routes, the discretized interval of transportation volume can also be used to allocate transportation resources more effectively.

In order to verify the accuracy and reliability of the test results, 20 repeated operations were performed on each test sample in the same software and hardware environment, and the average score of these operations was used to represent the performance of the algorithm. Subsequently, a detailed comparative analysis was conducted between this average result and the results obtained using other algorithms. For a comparison of algorithm search efficiency, please refer to Figure 5.

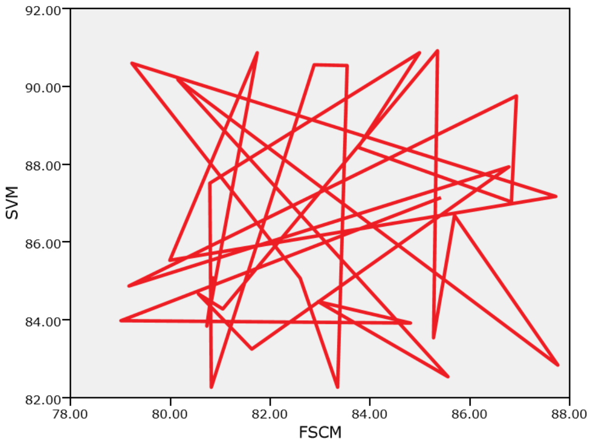

Figure 5: Search efficiency of different algorithms.

To reduce the interference of random errors and occasional events on the results, multiple repeated calculations were conducted for each case in a consistent software and hardware environment. This can more accurately evaluate the performance of the algorithm. Compared to SVM, the obvious advantage of FSVM is that it can better cope with uncertainty and noise in data. When planning logistics paths, various uncertainties such as changes in road conditions and weather effects are often encountered. The relevant results are shown in Figures 6 and 7. Compared with traditional SVM algorithms, FSVM has shown significant superiority in performance.

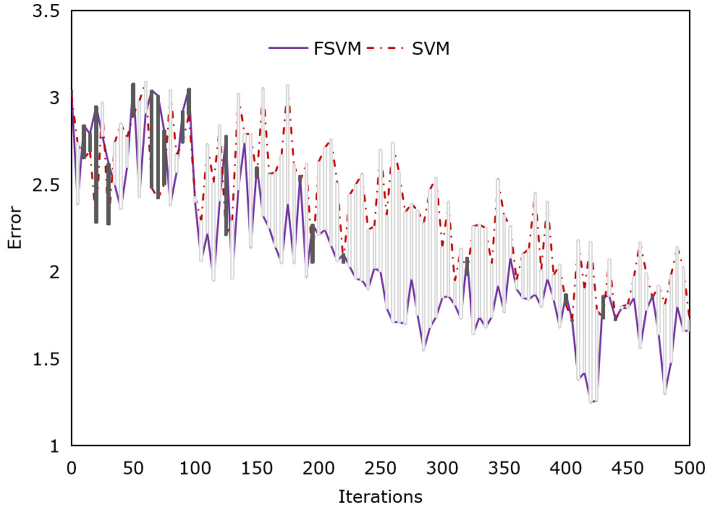

Figure 6: Algorithm error test.

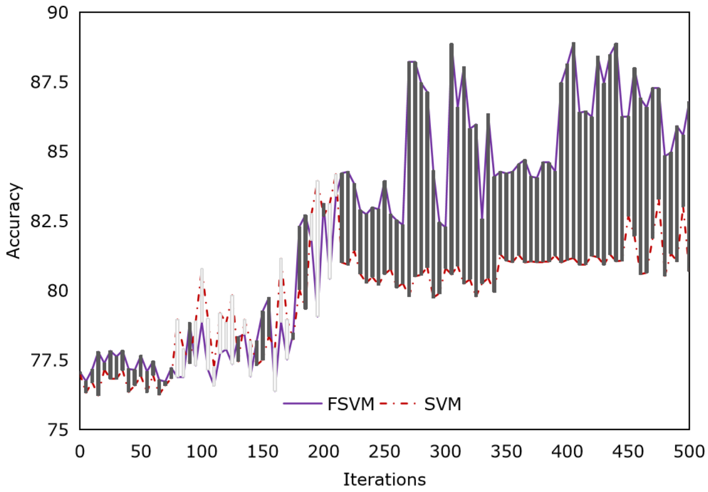

Figure 7: Algorithm accuracy testing.

FSVM found that its accuracy was effectively improved by 32.7% in the process of network transportation, and in the analysis process of reducing logistics, it was found that a unique learning mechanism brought high transportation efficiency to optimal logistics transportation. This not only proves the mechanism of its learning mode but also makes effective improvement plans for reducing logistics costs.

6 CONCLUSIONS

This study successfully constructed an intelligent logistics management system based on CAD and FSVM and conducted an in-depth evaluation of its comprehensive performance. Research data shows that the system performs well in dealing with complex logistics path planning problems. Compared with traditional SVM algorithms, FSVM has not only made breakthroughs in search efficiency but also made significant progress in error control and accuracy improvement - with an error reduction of up to 32.17% and an accuracy improvement of 13.47%. These significant advantages mean that in practical operation, the intelligent logistics management system can lock in the best logistics path more quickly and accurately, thereby effectively improving logistics efficiency and reducing operating costs.

Integrating the results of this research into teaching activities in the field of logistics management not only allows teachers to showcase cutting-edge technologies and efficient algorithms in the field of logistics management to students but also helps students deeply understand the core principles and technical requirements of logistics management. By hands-on operation of this intelligent system, students will greatly enhance their ability to solve practical logistics problems.

This research result not only provides solid support for the practical application of intelligent logistics management systems but also explores new possibilities for the application of the system in teaching. Looking ahead to the future, with the continuous innovation of technology and the continuous progress of teaching methods, intelligent logistics management systems will undoubtedly play an increasingly important role in the field of logistics management education.

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