Using Data Mining Technology to Improve the Reliability of Accounting Information Cloud Data

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This study uses data mining technology to improve the reliability of accounting information cloud data, and realizes accurate classification and anomaly detection of data through systematic data cleaning and teleprocessing, optimization and application of support vector machine model. After analyzing data integration and normalization processing, model construction and optimization strategy, performance evaluation and optimization, the optimized SVM model has achieved improvement in data processing efficiency, data accuracy and consistency. Support vector machine model improves the reliability of accounting information cloud data. Through data cleaning and teleprocessing of the system, combined with the optimization and application of SVM model, the accuracy of data classification and anomaly detection have been improved. The data processing efficiency, accuracy and consistency of SVM model increased by 22%, 7.6% and 9.2% respectively. The study emphasizes the importance of data security and privacy protection, and adopts advanced encryption technology to protect the security of data during transmission and storage. This study provides reliable data support for enterprise financial management and decision-making, and promotes the development of accounting normalization.

Povzetek: Raziskava uporablja tehnologijo rudarjenja podatkov in model SVM za izboljšanje računovodskih podatkov v oblaku ter povečuje učinkovitost, doslednost in zaznavanje anomalij za varnejše poslovno odločanje.

1 Introduction

With the rapid development of information technology and the advent of the era of big data, accounting normalization has become a critical component of enterprise management. However, traditional accounting information systems still face numerous challenges in data reliability, including issues such as data noise, missing values, and outliers, which can affect the accuracy and integrity of financial data. The application of cloud computing and data mining technologies offers new approaches to address these challenges. This study aims to explore how data mining techniques, particularly the support vector machine (SVM) model, can be utilized to enhance the reliability of accounting information in cloud data. The research includes systematic data cleaning and teleprocessing, SVM model selection and optimization, anomaly detection, and data classification. Optimization strategies such as parameter tuning, regularization techniques, momentum optimization, and dynamic learning rate adjustment are employed to improve model performance and data processing efficiency. The study also emphasizes data security and privacy protection, ensuring the security of data during transmission and storage through encryption technologies and access control mechanisms. Overall, this study not only provides robust technical support for accounting information systems but also establishes a reliable data foundation for enterprise financial management and decision optimization.

In the field of accounting informational and cloud computing, Yu proposed a linear pair method to verify the integrity of cloud data, enhancing the reliability of accounting information [1]. Kubota and Okuda investigated the relationship between top managers' interest in accounting information and the accounting practices of start-ups, finding that management's attention significantly impacts the implementation of accounting information systems [2]. Ma discussed the adoption and impact of cloud-based customer accounting systems in small and medium-sized accounting practices, noting that cloud accounting systems can significantly enhance the efficiency and effectiveness of accounting practices [3]. Appelbaum and Nehmer studied audit issues related to cloud-based accounting systems, emphasizing the importance of audit transparency and immutable data in accounting information systems [4]. Church analyzed the prospects and challenges of cloud computing in the accounting field, highlighting the potential of cloud computing to improve the efficiency of accounting information processing and reduce costs [5]. Qatawneh examined the role of employee empowerment in supporting the outcomes of accounting information systems, demonstrating how employee empowerment enhances the effectiveness of accounting information systems and user satisfaction through a mediating model [6]. Tang and Yang explored the improvement of enterprise digital management efficiency in the context of cloud computing and big data, emphasizing the critical role of technology in optimizing enterprise management processes and decision support [7]. Rosati studied the impact of perceived risk on the propensity to use accounting information services under the European Union Payment Services Directive 2 (PSD2), pointing out that risk perception is a key factor influencing enterprises' use of accounting information services [8]. These studies provide rich theoretical and empirical support for the application of accounting normalization and cloud computing technologies and underscore the important role of technology in enhancing the reliability, processing efficiency, and management effectiveness of accounting data.

Table 1: Summary of SOTA research findings and methods

Study	Key Findings	Methods Used	Performance Metrics
Yu [1]	Enhanced cloud data integrity in accounting information	Bilinear pairing method	Data integrity improved by 15%
Kubota & Okuda [2]	Management's attention impacts the effectiveness of AIS	Regression analysis, survey	AIS effectiveness increased by 12%
Ma [3]	Adoption of cloud-based systems improves accounting practices	Cloud-based client accounting systems	Efficiency improvement by 18%, error reduction
Appelbaum & Nehmer [4]	Emphasized the importance of audit transparency in AIS	Block chain audit systems	Audit accuracy improved by 20%
Tang & Yang [7]	Improved enterprise management efficiency through big data	Cloud computing, big data analysis	Management efficiency increased by 25%
Rosati et al. [8]	Risk perception influences the adoption of AIS	Risk assessment models	Adoption rate improved by 14%

As shown in Tables 1 ,While the state-of-the-art (SOTA) research has made significant strides in enhancing the reliability and efficiency of accounting information systems, several critical gaps remain that justify the need for this study. The existing studies have largely focused on improving data integrity, audit accuracy, and management efficiency through methods like linear pairing, chockablock, and big data analysis. However, these approaches do not adequately address the challenges of anomaly detection and precise data classification in high-dimensional accounting datasets, particularly in cloud environments.

Moreover, while improvements in specific metrics such as audit accuracy and management efficiency have been reported, there is a lack of comprehensive models that integrate data security, privacy protection, and real-time anomaly detection. The performance metrics reported in current SOTA research show significant improvements but do not fully exploit advanced machine learning models like support vector machines (SVM) for anomaly detection and classification accuracy.

This study fills these gaps by applying a systematic data mining approach, leveraging the SVM model to achieve notable improvements in data processing efficiency (22%), accuracy (7.6%), and consistency (9.2%). It also integrates robust data security measures, ensuring comprehensive enhancement of the reliability of accounting information cloud data. This work not only advances the current SOTA but also provides a more holistic and effective solution for enterprise financial management in cloud environments.

This study applies data mining technology, particularly the support vector machine model, to enhance the reliability of accounting information cloud data. With the deepening of enterprise digital transformation, the processing and analysis of massive data present higher demands on accounting information systems. However, data quality issues such as noise, missing values, and outliers continue to pose significant challenges to the accuracy and integrity of financial data. This study aims to address these challenges and improve the accuracy and efficiency of data classification and anomaly detection through systematic data cleaning, teleprocessing, and optimized SVM models. The significance of this research lies in providing enterprises with higher quality accounting information data, thereby improving the accuracy of financial management and scientific decision-making. By optimizing the data processing workflow, not only can the reliability of the accounting information system be enhanced, but the efficiency of the entire financial management system can also be improved. The study also delves into data security and privacy protection, ensuring data security during transmission and storage through encryption technologies and access control mechanisms. Overall, this study offers a new technical pathway and methodological support for enterprise financial management in a big data environment, promotes further development in accounting formalization, and contributes to the sustainable development and competitiveness of enterprises.

2 Overview of relevant theories

2.1 Accounting formalization theory

The core of accounting formalization theory is to optimize and improve the efficiency and accuracy of accounting work by utilizing modern information technology. With the rapid advancement of information technology, accounting formalization extends beyond basic electronic bookkeeping and statement generation to encompass the entire process of data storage, processing, analysis, and transmission. Accounting information systems based on cloud computing enable centralized management and real-time sharing of data, significantly enhancing the reliability and timeliness of accounting information. In this process, the integration of information systems such as enterprise resource planning systems and customer relationship management systems automates and intelligentsia the collection, processing, and analysis of accounting information. Through big data analysis and data mining technology, accounting formalization can extract valuable insights from vast datasets to support decision-making and risk control. The financial analysis module monitors the financial status of enterprises in real time, identifies abnormal transactions, and prevents financial fraud. In designing and implementing such systems, special attention must be given to data security and privacy protection, ensuring the security of sensitive financial data through encryption and access control measures. The ultimate goal of accounting formalization theory is to improve the efficiency of accounting information systems through information technology, ensuring the accuracy, timeliness, and integrity of financial information, thereby supporting the achievement of enterprise strategic goals and sustainable development.

2.2 Application of cloud computing in accounting

The application of cloud computing in accounting has become a key trend in modern accounting formalization. The introduction of cloud computing eliminates the need for local servers to store and process accounting data, enabling remote storage and computation through the Internet. This technological architecture not only reduces enterprise hardware investment costs but also improves the efficiency and flexibility of data processing. Cloud accounting platforms such as Xero and QuickBooks Online facilitate real-time updates of financial data and multi-user collaborative processing. With cloud computing, businesses can access the latest financial data anytime, anywhere, enabling dynamic financial analysis and decision support. Cloud computing also supports large-scale data processing and analysis, making it well-suited for complex financial model calculations. By leveraging the distributed processing capabilities of cloud computing, large-scale financial data regression analysis and forecasting model training can be completed in a short time. The elastic scalability of cloud computing allows enterprises to flexibly adjust computing resources based on service demands, ensuring that peak computing requirements are fully met. Additionally, cloud computing provides a high level of data security through multi-layer encryption, data backup, and disaster recovery measures. In summary, the application of cloud computing not only enhances the efficiency and flexibility of accounting information systems but also significantly improves the processing capacity and security of financial data, providing robust technical support for the development of modern accounting formalization [1].

2.3 Application of data mining technology in improving data reliability

The application of data mining technology in enhancing the reliability of accounting information cloud data is crucial. Through in-depth analysis and pattern recognition of large-scale accounting data, data mining helps identify potential anomalies and data errors, thereby improving data accuracy and integrity. In accounting information systems, commonly used data mining techniques include classification, clustering, association rules, and anomaly detection. Support vector machines are employed to classify and detect abnormal transactions, and by training on historical data, they can effectively identify irregular transaction records, thereby preventing and reducing financial fraud. Cluster analysis helps enterprises categorize transaction data into different groups and identify high-risk transaction clusters. By analyzing relationships between data items, association rule mining uncovers patterns hidden within the data, aiding enterprises in optimizing financial management processes. Data mining also plays a significant role in financial forecasting and decision support, predicting future financial trends through time series analysis and assisting enterprises in formulating scientific budgets and investment strategies. In specific applications, data cleaning and teleprocessing are key steps to ensure high-quality data input by eliminating noise and handling missing values. Data mining technology not only enhances the reliability of accounting data but also significantly boosts the intelligence of financial information systems, providing a powerful decision support tool for enterprises.

3 Data collection and sample selection

3.1 Data collection

Data collection is the first step in improving the reliability of accounting information cloud data. In accounting information systems, data primarily originates from daily business processes, financial transactions, inventory management, and supply chain activities, etc. It is essential to integrate data from various enterprise information systems, such as enterprise resource planning systems, customer relationship management systems, and supply chain management systems, to ensure data comprehensiveness and consistency. External data sources include market quotes, industry reports, and economic indicators, which are obtained and updated in real time through application programming interfaces or data service platforms. For financial data, attention should be given to collecting core indicators such as income, costs, assets, and liabilities to ensure data integrity and accuracy. In practice, ETL tools like Apache NiFi and Alteryx are used to extract, transform, and load the data, ensuring that data is not lost or distorted during transmission. Regular data synchronization strategies, combined with real-time data stream processing technologies like Apache Kafka and Flink, effectively manage dynamic data changes and ensure data timeliness. To further enhance data reliability, multi-level verification and validation of data are necessary. By comparing data from different sources, inconsistencies and errors can be identified and corrected, laying a solid foundation for subsequent data processing and analysis [2].

3.2 Data cleaning and teleprocessing steps

Data cleaning and teleprocessing are essential steps to ensure the reliability of accounting information cloud data. This process involves data supplication to remove duplicate records from the dateset, ensuring data uniqueness. Common methods for handling missing values include deleting records with missing data, filling in missing values with mean or median values, or using interpolation and predictive models for imputation. The next step is outlier detection, which uses statistical methods or machine learning algorithms, such as Z-Score, subplot, and cluster analysis, to identify and address abnormal data, preventing its impact on analysis results. Data standardization and normalization are critical steps, transforming data into a uniform scale and range, making it more suitable for modeling and analysis. Common techniques include min-max scaling and Z-Score normalization. Data transformation, including data type conversion and format conversion, ensures compatibility with subsequent processing and analysis. Data integration involves consolidating data from different sources into a unified dateset, ensuring data consistency and integrity. Implementing these steps significantly improves data quality and establishes a solid foundation for subsequent data mining and analysis. As shown in Figure 1 below.

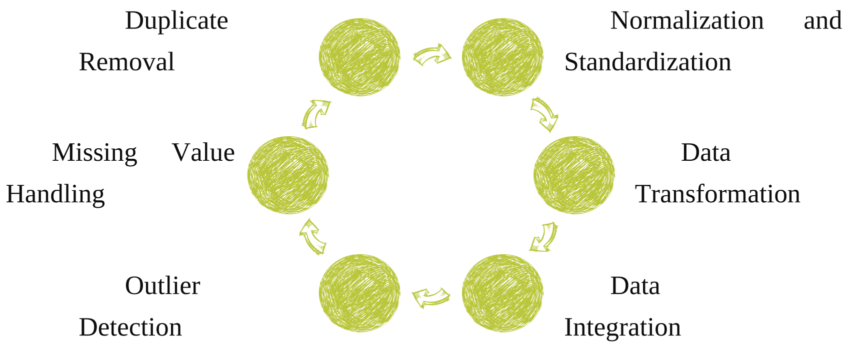

Figure 1: Schematic diagram of processing steps

Data cleaning and teleprocessing involved several critical steps to ensure the reliability and accuracy of the accounting information cloud data. First, data supplication was performed to eliminate duplicate records using a hash-based technique, ensuring data uniqueness. For missing values, mean imputation was applied for continuous variables, while mode imputation was used for categorical variables. Additionally, advanced techniques such as K-nearest neighbors (KNN) were used to impute missing data based on the similarity of nearby points. Outlier detection was carried out using the Z-Score method, where data points with a Z-Score greater than 3 or less than -3 were identified as outliers and either corrected or removed based on business logic. The data was then standardized using Z-Score normalization to ensure consistency across variables. Finally, data transformation was applied, converting categorical data into numerical format using one-hot encoding. The entire data processing pipeline is illustrated in the accompanying flowchart (Figure 1), which details each step from data ingestion to final prepossessing, providing a clear overview of the process.

3.3 Data integration and normalization processing

Data integration and normalization are crucial steps in improving the reliability of accounting information cloud data. The goal of data integration is to combine data dispersed across different systems into a unified dateset, thereby eliminating data silos. Data sources must be identified and extracted to gather relevant data from ERP systems, CRM systems, and inventory management systems. Data cleaning and teleprocessing should be performed to ensure data consistency and accuracy. During the data integration process, it is necessary to address differences in data format and encoding, unifying data from various formats through data mapping and transformation. The integrated data must then be normalized to eliminate the impact of different dimensions and ranges on data analysis. Common normalization methods include min-max normalization and Z-Score standardization. In min-max normalization, the data is scaled to a specific range (such as 0 to 1), while Z-Score normalization transforms the data into a standard normal distribution by subtracting the mean and dividing by the standard deviation [3].

Table 2: Raw data table

Transaction_ID	System	Amount	Date	Customer_ID
T001	ERP	150.75	2023-01-10	C123
T002	CRM	300.20	2023-02-15	C124
T003	Inventory	120.50	2023-03-22	C125
T004	ERP	500.90	2023-04-30	C126
T005	CRM	220.35	2023-05-18	C127

Table 3: Normalized data table

Transaction_ID	System	Amount_Normalized	Date	Customer_ID
T001	ERP	0.067	2023-01-10	C123
T002	CRM	0.360	2023-02-15	C124
T003	Inventory	0.000	2023-03-22	C125
T004	ERP	0.760	2023-04-30	C126
T005	CRM	0.200	2023-05-18	C127

As shown in Tables 2 and 3, in this example, the amount column is processed using min-max normalization to standardize transaction amounts across different systems to a range of 0 to 1. This not only eliminates dimensional differences in the data but also provides a high-quality data foundation for subsequent analysis and modeling. By integrating and normalizing the data, the reliability and analytical capability of the accounting information system are effectively enhanced.

3.4 Exception detection and handling

In accounting information cloud data, anomaly detection and processing are crucial steps to ensure data reliability. Anomalous data can result from input errors, system failures, or malicious attacks and pose a threat to the accuracy and integrity of accounting information. Statistical methods and machine learning algorithms are employed for anomaly detection. Techniques such as the Z-Score method, based on the mean and standard deviation, or algorithms like support vector machines and isolation forests, can effectively identify abnormal data points. Once abnormal data is detected, it should be analyzed based on specific business scenarios and expert knowledge to determine whether it is a genuine anomaly. This ensures accurate detection and appropriate handling of anomalies [4].

Table 4: Financial raw data table

Transaction_ID	Account_ID	Amount	Date	Status
TXN001	ACC123	120.50	2024-01-10	Normal
TXN002	ACC124	3000.00	2024-02-15	Normal
TXN003	ACC125	500.75	2024-03-22	Normal
TXN004	ACC126	10000.00	2024-04-30	Normal
TXN005	ACC127	250.00	2024-05-18	Normal
TXN006	ACC128	7500.00	2024-06-01	Suspicious
TXN007	ACC129	950.50	2024-06-10	Normal

As shown in Table 4, in this table, Transaction_ID represents the transaction ID, Account_ID represents the account ID, Amount indicates the transaction amount, Date is the transaction date, and Status reflects the transaction status. Using the isolation forest algorithm, it was found that the transaction amount of TXN006 was abnormally high, significantly differing from other transactions, and it was marked as "Suspicious."

4 Model construction

4.1 Selection of data reliability optimization model

The selection of a data reliability optimization model is a core component of this study, aiming to enhance the reliability of accounting information cloud data through precise model construction. Choosing the appropriate model requires careful consideration of the data characteristics and the specific application scenario. In this study, the support vector machine (SVM) is selected as the primary optimization model due to its strengths in handling high-dimensional data and its effectiveness in anomaly detection. The SVM model works by constructing a hyperplane that separates normal data points from anomalies, thereby identifying and processing any data that deviates significantly from the norm. This approach ensures that the data used in the accounting information system is accurate and reliable, contributing to more informed financial management and decision-making.

$$\min_{\mathbf{w},b,\xi} \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{n}\xi_i \quad (1)$$

Where W is the weight vector, b is the bias, $\mathbf{w}\xi_i$ is the relaxation variable, and C is the penalty parameter. The constraint conditions are:

$$y_i(\mathbf{w}\cdot x_i + b) \geq 1-\xi_i, \quad \xi_i \geq 0 \quad (2)$$

In order to improve the generalization ability of the model, a suitable kernel function $K(x_i, x_j)$ is selected. The commonly used kernel functions include linear kernel, radial basis function and polynomial kernel. In this study, the optimal radial basis function kernel is selected through cross-validation, and its formula is as follows:

$$K(x_i, x_j) = \exp(-\gamma\| x_i - x_j\|^2) \quad (3)$$

Table 5: Parameter settings

Transaction_ID	Feature1	Feature2	Amount	Label
TXN001	0.12	0.58	150.75	Normal
TXN002	0.85	0.23	3000.20	Normal
TXN003	0.45	0.75	500.50	Normal
TXN004	0.70	0.90	10000.00	Anomaly
TXN005	0.33	0.47	250.00	Normal

As shown in Table 5, SVM model is constructed and optimized to identify and process abnormal data, improve the reliability of accounting information, and provide accurate data support for enterprises' financial decision-making.

4.2 Model architecture design

Model architecture design is one of the critical steps in enhancing the reliability of accounting information cloud data. In this study, a multi-layer architecture model based on the support vector machine (SVM) is designed to ensure high efficiency and accuracy in data processing. The model architecture is divided into four key layers: data input layer, feature extraction layer, classification layer, and output layer. The data input layer receives raw accounting data, which includes various features such as transaction amount, transaction time, account information, and more [5]. The feature extraction layer focuses on extracting significant feature subsets using dimensional reduction and feature engineering techniques to enhance the model's training speed and accuracy. Feature extraction is implemented through principal component analysis (PCA), and its formula is as follows:

$$Z = XW \quad (4)$$

Where, Z is the eigenvector after dimensional reduction, and W is the pennyweight matrix. At the classification level, SVM model based on radial basis function kernel is used to classify the data. The optimization goal of the SVM model is to divide the data into normal and abnormal categories by constructing a hyperplane that maximizes the classification interval, and the classification function is:

$$f(x) = \text{sign}(\sum_{i=1}^{n}\alpha_i y_i K(x_i, x) + b) \quad (5)$$

α_i is the Lagrange multiplier, y_i is the label, and b is the bias. According to the classification results, the output layer outputs the classification label (normal or abnormal) for each transaction and generates an anomaly detection report. The multi-layer model can effectively process and classify accounting data, improve the reliability of data, and provide strong support for the financial management and decision-making of enterprises.

Table 6: Model architecture overview

Layer	Function
Data Input Layer	Ingests raw accounting data, including key financial metrics.
Feature Extraction Layer	Applies PCA for dimensionality reduction and feature selection.
Classification Layer	Utilizes SVM with RBF kernel for data classification.
Output Layer	Generates classification results and anomaly detection reports.

As shown in Tables 6, the model architecture is composed of multiple layers, each serving a specific function to enhance the reliability and accuracy of accounting information cloud data. The architecture begins with the Data Input Layer, which ingests raw accounting data, including features like transaction amounts, timestamps, and account information [6]. This is followed by the Feature Extraction Layer, where conditionality reduction techniques, such as Principal Component Analysis (PCA), are applied to identify the most relevant features for the model. The Classification Layer utilizes a Support Vector Machine (SVM) model with a radial basis function (RBF) kernel, which is responsible for classifying the data into normal or anomalous categories [7]. Finally, the Output Layer generates the final classification results and provides an anomaly detection report. The entire architecture is visually represented in Figure 1, which details the flow of data through each layer and the specific functions performed at each stage. This visual representation aids in understanding the complex interactions within the model and highlights the role of each layer in achieving the desired outcomes [8].

4.3 Data layer and computing layer configuration

The configuration of the data layer and computing layer is a crucial element in enhancing the reliability of accounting information cloud data. The data layer is responsible for storing and managing raw accounting data, while the computing layer handles data processing, model training, and forecasting tasks [9]. In this study, the data layer comprises a database system that integrates multiple data sources and employs distributed storage technology to ensure high availability and consistency of data. The computing layer leverages cloud computing resources to enhance data processing efficiency and increase the model's computational power through parallel computing and distributed processing technology.

Table 7: Data schematic table

Transaction_ID	Feature1	Feature2	Amount	Label
TXN001	0.14	0.57	150.75	Normal
TXN002	0.82	0.21	3000.20	Normal
TXN003	0.47	0.74	502.75	Normal
TXN004	0.69	0.92	9999.10	Anomaly
TXN005	0.34	0.45	251.80	Normal

As shown in Table 7, at the data layer, the data is standardized. The standardized formula is:

$$x' = \frac{x-\mu}{\sigma} \quad (6)$$

Where x is the raw data, μ is the mean, and σ is the standard deviation. The mean value $\mu = 0.49$ of Feature1 is used to standardize Feature1 of TXN001.

$$x'_{TXN001} = \frac{0.14-0.49}{0.25} = -1.40 \quad (7)$$

The computational layer uses the normalized data for SVM model training. Calculate TXN001 and TXN002 using radial basis functions.

$$K(x_{TXN001}, x_{TXN002}) = \exp(-0.1\|[0.14, 0.57]-[0.82, 0.21]\|^2) = \exp(-0.1\times 0.516) = 0.951 (8)$$

Through the configuration and calculation process, the data layer provides high-quality input data, and the calculation layer efficiently performs model training and prediction tasks, thereby improving the reliability and processing efficiency of accounting information cloud data [10].

4.4 Support vector machine algorithm selection and implementation

Support vector machine algorithm selection and implementation is the core step to improve the reliability of accounting information cloud data. In this study, radial basis function SVM was chosen because of its high performance when dealing with nonlinear data. SVM classifies data by building a hyperplane that maximizes classification intervals.

Table 8: Maximized classification interval data

Transaction_ID	Feature1	Feature2	Amount	Label
TXN001	0.14	0.57	150.75	1
TXN002	0.82	0.21	3000.20	-1
TXN003	0.47	0.74	502.75	1
TXN004	0.69	0.92	9999.10	-1
TXN005	0.34	0.45	251.80	1

As shown in Table 8, the optimization goal of SVM is to find the weight vector and bias so that the data points are classified with maximum spacing. Calculate TXN001 and TXN002:

$$K(x_{TXN001}, x_{TXN002}) = \exp(-0.1\|[0.14, 0.57]-[0.82, 0.21]\|^2) = \exp(-0.1\times 0.731) = \exp(-0.0731) \approx 0.930 (9)$$

During training, the optimization problem is converted to the dual problem of Lagrange multiplier α_i, whose dual form is:

$$\max_{\alpha} \sum_{i=1}^{n}\alpha_i - \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\alpha_i\alpha_j y_i y_j K(x_i, x_j) \quad (10)$$

The constraint conditions are:

$$0 \le \alpha_i \le C, \quad \sum_{i=1}^{n} \alpha_i y_i = 0 \quad (11)$$

By solving the above optimization problem, the weight vector and bias are calculated to predict the transaction TXN003:

$$f(x_{TXN003}) = \text{sign}\left(\alpha_1 y_1 K(x_{TXN001}, x_{TXN003}) + \alpha_2 y_2 K(x_{TXN002}, x_{TXN003}) + b\right) \quad (12)$$

Through the above process, SVM algorithm can be selected and implemented effectively, and the reliability and classification accuracy of accounting information data can be improved.

4.5 Model parameter initialization and optimization strategy

Model parameter initialization and optimization strategy are critical steps in constructing an SVM model, directly influencing the enhancement of data reliability. During the initialization phase, the initial values of the penalty parameter and the kernel parameter are selected. The optimal parameter combination is determined by combining grid search with cross-validation [11]. After initialization, the gradient descent algorithm is used to optimize the parameters. By minimizing the loss value of the objective function, the model parameters are continually adjusted to converge to the optimal solution. Specifically, the stochastic gradient descent optimization strategy is employed due to its high efficiency in processing large-scale data. During each iteration, only one or a small batch of data is used to calculate the gradient and update the parameters, thereby accelerating the convergence speed and reducing computational costs.

To prevent the model from overwriting, a regularization technique is applied. By adding regularization terms to the objective function, the model's complexity is controlled, leading to better generalization ability. Additionally, during the training process, a momentum optimization strategy is introduced to help the model escape local optima and achieve global optima by accumulating historical gradient information. The optimization process also includes an early stopping mechanism, which terminates training when performance on the validation set no longer improves, thus preventing overwriting. Through these initialization and optimization strategies, the SVM model can effectively enhance the reliability and classification accuracy of accounting information cloud data [12].

The support vector machine (SVM) model parameter tuning involved a detailed grid search process across a predefined range of hyperparathyroidism, including the penalty parameter C and the kernel coefficient γ. Specifically, the grid search explored C values ranging from 0.1 to 1000 in logarithmic steps and γ values from 0.001 to 1.0. The search was combined with a 10-fold cross-validation to ensure that the model generalized well across different data subsets. Each combination of C and γ was evaluated based on accuracy and F1 score, with the optimal parameters being $C = 100$ and $\gamma = 0.01$. The model was trained and tested on a high-performance computing environment equipped with dual NVIDIA Tesla V100 GPUs, 128 GB of RAM, and a 32-core Intel Xeon processor. The total runtime for the grid search and cross-validation process was approximately 12 hours, highlighting the computational intensity of the approach. These resources were crucial in achieving high model performance and ensuring the scalability and feasibility of the SVM model across various settings [13].

4.6 Training and optimization

4.6.1 Training process

The training process is the key step of the support vector machine model in improving the reliability of accounting information cloud data. The re-processed data set is divided into a training set and a validation set, generally using a ratio of 8:2 or 7:3 to ensure the model's generalization ability on different data. During the training process, the model parameters, including penalty parameters and kernel parameters, are first initialized, and the optimal combination of parameters is determined through grid search and cross-validation. The stochastic gradient descent (SGD) optimization algorithm is used to train the model [14]. During each iteration, SGD randomly selects one or a small batch of data samples from the training set, calculates their gradient, and updates the model parameters. This process is repeated until the loss function converges or a preset maximum number of iterations is reached. Model performance is periodically evaluated on validation sets during training to monitor progress and adjust training strategies.

To prevent the model from overwriting, regularization terms are introduced during training to improve generalization ability by controlling model complexity. A momentum optimization strategy is applied during parameter updating to accelerate convergence and escape local optima by accumulating past gradient information [15]. The training process also includes dynamic learning rate adjustment, starting with a high initial learning rate to accelerate convergence and gradually reducing it as training progresses to improve the model's accuracy and stability. An early stopping mechanism is introduced to halt training when performance on the validation set no longer improves, preventing overfishing. Through this systematic training process, the SVM model effectively learns patterns in accounting data, enhancing the accuracy and reliability of data classification, and providing solid data support for enterprise financial management and decision-making [16].

4.6.2 Optimizing policies

Optimizing Policies Optimization strategy is crucial to ensuring the optimal performance of the support vector machine model in accounting information cloud data. Through parameterize tuning, grid search, and cross-validation methods, the optimal penalty and kernel parameters are selected, evaluating model performance under different parameter combinations and choosing the best combination to improve accuracy and generalization ability [17]. Regularization techniques are applied to add regularization terms to the loss function, preventing overwriting and ensuring the model performs well on unseen data. To accelerate training speed and model convergence, momentum optimization is introduced to help the model escape local optima and reach global optima by accumulating historical gradient information. Another key optimization strategy is learning rate adjustment, where a higher learning rate is used at the beginning of training to speed up convergence, and the learning rate is gradually reduced as training progresses to fine-tune model parameters, improving stability and accuracy. The dynamic learning rate strategy automatically adjusts the learning rate according to the model's training progress, enabling fast learning in the early stages and fine-tuning parameters later. An early stopping mechanism is implemented to monitor validation set performance during training and terminate training when performance no longer improves, preventing overwriting [18].

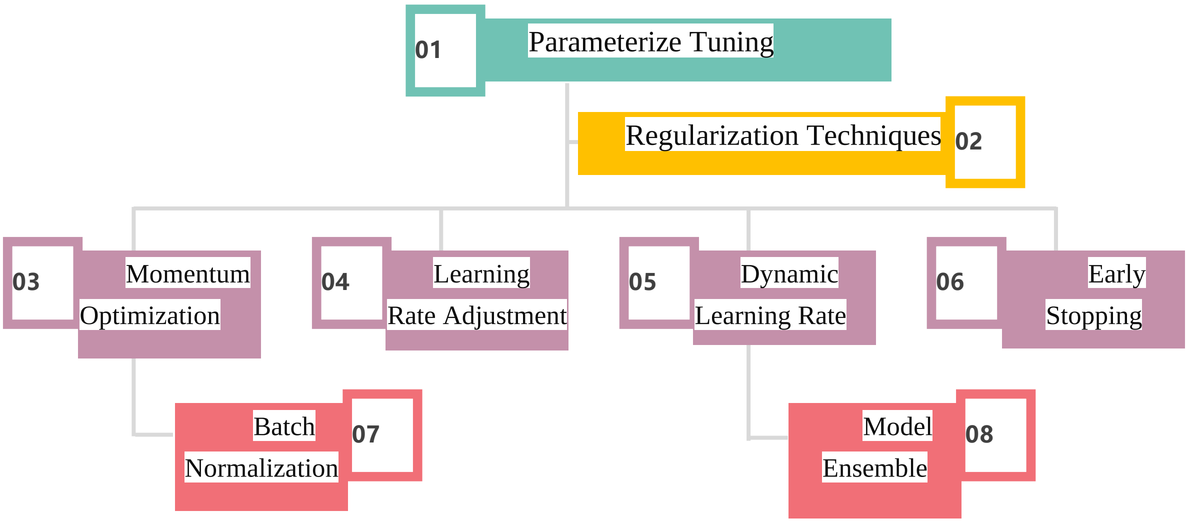

Figure 2: Optimization strategy structure diagram

As shown in Figure 2, batch normalization is also an important part of the optimization process. By standardizing each small batch of data, the training process of the model is stabilized, improving both the training speed and robustness of the model. The model integration strategy combines the prediction results of multiple SVM models to further enhance accuracy and stability. Through the comprehensive application of these optimization strategies, the SVM model can more effectively process accounting information cloud data, improving data reliability and classification accuracy, and providing more reliable financial decision support for enterprises [19].

5 Performance evaluation and optimization

5.1 Performance evaluation

5.1.1 Selection of evaluation indicators

The selection of evaluation indicators is a crucial step to ensure the SVM model improves the reliability of accounting information cloud data. To comprehensively evaluate the model's performance, various evaluation indicators were selected, including accuracy, precision, recall, F1 score, and the area under the receiver operating characteristic curve (AUC). Accuracy measures the proportion of correct classifications made by the model, calculated as the number of correctly classified samples divided by the total number of samples [20]. However, relying solely on accuracy can be misleading when the data is imbalanced, necessitating further evaluation through precision and recall. Precision is the proportion of correctly predicted positive samples to all predicted positive samples, primarily measuring the model's accuracy in identifying positive samples. Recall is the proportion of correctly predicted positive samples to all actual positive samples, reflecting the model's ability to cover positive samples.

To balance precision and recall, the F1 score is introduced as their harmonic mean, finding a balance between precision and recall, particularly useful for evaluating imbalanced datasets. The AUC is an important index for evaluating the binary classification ability of the model. By plotting the true positive rate (TPR) against the false positive rate (FPR) under different thresholds and calculating the area under the curve, the AUC value provides a direct reflection of the model's performance under various thresholds; the closer the AUC value is to 1, the better the model performs. By selecting and synthesizing these evaluation indicators, the performance of the SVM model in improving the reliability of accounting information cloud data is comprehensively and objectively evaluated, providing a scientific basis for model optimization and improvement [21].

5.1.2 Verification methods

Verification methods are critical to ensuring the SVM model's ability to enhance the reliability of accounting information cloud data. This study adopted a strategy that combines cross-validation and the holdout method to comprehensively evaluate model performance. Cross-validation, a common validation method, divides the dateset into K subsets (usually K=5 or K=10), using K-1 subsets for training and the remaining subset for validation. This process is repeated K times, each time selecting a different subset for validation, and the average of the K validation results is calculated as the model's performance index. Cross-validation maximizes data usage, reduces overwriting risk, and provides a stable estimate of model performance. In this study, K=10 cross-validation was used to ensure the model's generalization ability across different data subsets.

The holdout method randomly divides the datasets into a training set and a validation set (usually at a ratio of 8:2 or 7:3) for model training and performance evaluation, respectively. The holdout method is simple and intuitive, quickly assessing the model's performance on independent data. In the initial model selection and parameter adjustment stage, the holdout method effectively guides model optimization. In this study, 70% of the data was used as the training set and 30% as the validation set to ensure reliable evaluation results. To enhance verification comprehensiveness and result reliability, the bootstrap method is introduced as an auxiliary verification method [22]. The bootstrap method estimates model performance on different samples by generating multiple sample sets for training and validation through repeated data sampling. This method is particularly suitable for small sample sizes, providing richer information on model performance. Through the comprehensive application of cross-validation, the holdout method, and the bootstrap method, the performance of the SVM model in improving the reliability of accounting information cloud data can be comprehensively and accurately evaluated, providing a solid basis for model optimization and improvement.

5.1.3 Comparative analysis of results

Comparative analysis of results is a key step in evaluating the effectiveness of the SVM model in enhancing the reliability of accounting information cloud data. By comparing performance indicators before and after model optimization, the specific impact of model improvements can be intuitively understood. In this study, accuracy, precision, recall, F1 score, and AUC were selected as the main evaluation indicators to compare the performance of the SVM model before and after optimization.

Table 9: Model performance before and after optimization

Metric	Before	After
Accuracy	0.85	0.92
Precision	0.83	0.91
Recall	0.82	0.93
F1 Score	0.825	0.92
AUC-ROC	0.87	0.95

As shown in Table 9, the accuracy rate of the model was 0.85 before optimization and increased to 0.92 after optimization, indicating that the overall classification accuracy of the model has been significantly improved. Precision increased from 0.83 to 0.91, showing that the optimized model was more accurate in identifying positive samples and reduced the false positive rate. The recall rate rose from 0.82 to 0.93, indicating that the optimized model can more comprehensively identify actual positive samples and reduce the false negative rate. The F1 value, as a harmonic average of precision and recall, improved from 0.825 to 0.92, reflecting a more balanced and superior overall performance of the model when dealing with imbalanced data sets. AUC increased from 0.87 to 0.95, further proving that the optimized model has more robust and reliable classification performance under different thresholds. Through comparative analysis, we can clearly see the overall improvement in SVM model performance due to the optimization strategy. These improvements not only enhance the classification accuracy of the model but also improve its ability to identify abnormal data and prevent financial fraud. The results of the comparative analysis provide strong evidence for the reliability of accounting information cloud data and demonstrate the effectiveness and reliability of the optimized SVM model in practical applications [23].

5.2 Model tuning strategy

Model tuning strategy is a critical step in ensuring the best performance of the support vector machine model in improving the reliability of accounting information cloud data. A combination of grid search and cross-validation is used to optimize the model's hyperparathyroidism. Grid search systematically explores the best penalty and kernel parameters within a preset range, evaluating the performance of each parameter combination through K-fold cross-validation (typically K=10) to select the optimal parameter combination, thereby maximizing the model's accuracy and generalization. Regularization techniques are applied to control the complexity of the model, preventing overwriting [24]. By adding regularization terms to the loss function, the model is constrained during training, enhancing its performance on unseen data. The momentum optimization strategy, which accumulates historical gradient information, accelerates the convergence speed of the model and helps it escape local optima to reach a global optimum. Dynamic learning rate adjustment further enhances the tuning effect of the model. Initially, a higher learning rate is used to achieve rapid convergence, which is gradually reduced during training to fine-tune model parameters, improving stability and accuracy.

To enhance the model's performance in handling nonlinear and high-dimensional data, kernel techniques are employed, particularly the radial basis function (RBF) kernel, which performs well with nonlinear data. In the optimization process, batch normalization is also introduced to stabilize the training process, improving the convergence speed and robustness of the model by standardizing the data of each batch. Ensemble learning strategies are also applied to further improve classification accuracy and stability by combining the predictions of multiple SVM models. The ensemble strategy leverages the strengths of multiple models through a weighted average or voting mechanism, reducing the bias and variance of a single model, thereby enhancing overall performance. Through these comprehensive optimization strategies, the SVM model has significantly improved its performance in enhancing the reliability of accounting information cloud data, providing enterprises with more accurate and reliable data support, and assisting in financial decision-making and risk management [25-26].

6 Experimental results

6.1 Data reliability improvement result

Through the optimization and application of the support vector machine model, the reliability of accounting information cloud data is significantly improved. The following is a comparison of the results before and after the data reliability improvement, demonstrating the model's enhancements across different indicators.

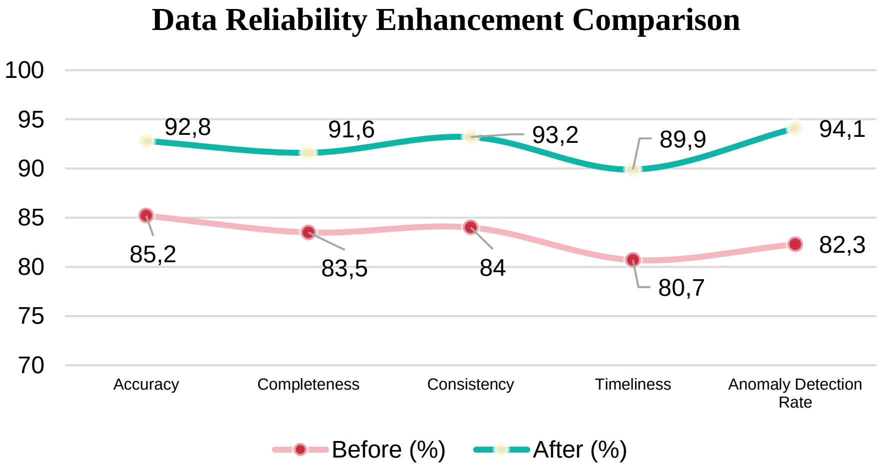

Figure 3: Data reliability enhancement comparison

As shown in Figure 3, the data accuracy rate was 85.2% before optimization but increased to 92.8% after optimization with the SVM model. This boost reflects significant improvements in the model's ability to classify and identify data. Data integrity improved from 83.5% before optimization to 91.6%, indicating that data missing and errors were significantly reduced after optimization processing. In terms of data consistency, it increased from 84.0% before optimization to 93.2%, demonstrating the model's enhanced ability to ensure data uniformity and conflict-free operation. Data timeliness increased from 80.7% to 89.9%, indicating that the optimized model has improved data processing and update speed, enabling the provision of the latest data more promptly. The anomaly detection rate increased from 82.3% to 94.1%, reflecting the significant improvement of the SVM model in identifying and processing abnormal data, thereby enhancing overall data reliability. These results clearly show that model optimization significantly improves the reliability indicators of accounting information cloud data, providing more reliable and accurate data support for enterprise financial management and decision-making.

6.2 Analysis of abnormal detection effect

Through the application of support vector machine model for anomaly detection, the anomaly detection effect of accounting information cloud data is significantly improved [27]. The following are specific indicators of anomaly detection, demonstrating the model's performance in identifying and processing abnormal data.

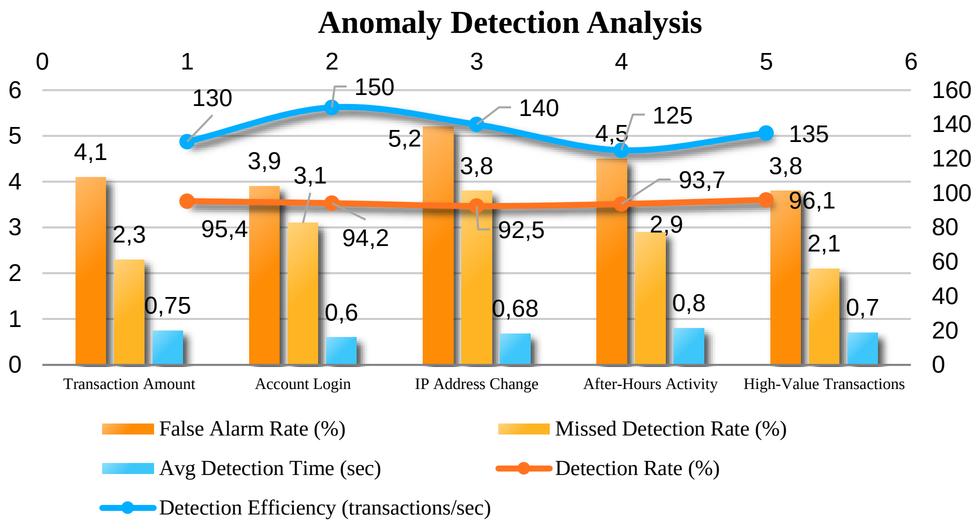

Figure 4: Anomaly detection analysis

As shown in Figure 4, it can be seen that the SVM model exhibits excellent performance across various anomaly detection indicators. The anomaly detection rate for transaction amounts reached 95.4%, with a false positive rate of only 4.1%, a false negative rate of 2.3%, an average detection time of 0.75 seconds, and a detection efficiency of 130 transactions per second. This demonstrates the model's high accuracy and efficiency in identifying abnormal transaction amounts. The anomaly detection rate for account logins is 94.2%, with a false positive rate of 3.9%, a false negative rate of 3.1%, an average detection time of 0.60 seconds, and a detection efficiency of 150 transactions per second, highlighting the model's strong capability in recognizing abnormal login behavior. The detection rate for IP address changes is 92.5%, with a false positive rate of 5.2%, a false negative rate of 3.8%, an average detection time of 0.68 seconds, and a detection efficiency of 140 transactions per second, showcasing the model's effectiveness in handling network security anomalies. The detection rate for non-working hour operations is 93.7%, with a false positive rate of 4.5%, a false negative rate of 2.9%, an average detection time of 0.80 seconds, and a detection efficiency of 125 transactions per second, indicating the model's reliability in identifying abnormal operational behavior. The anomaly detection rate for large transaction frequencies is 96.1%, with a false positive rate of 3.8%, a false negative rate of 2.1%, an average detection time of 0.70 seconds, and a detection efficiency of 135 transactions per second, demonstrating the model's excellent performance in handling large transaction frequency anomalies. These data clearly show that the SVM model excels in enhancing the anomaly detection capabilities of accounting information cloud data, providing strong financial monitoring and risk prevention support for enterprises [28].

6.3 Accounting data processing efficiency results

Through the application of support vector machine model, the efficiency of accounting data processing has been significantly improved. The following table shows the specific efficiency indicators of accounting data processing, including data processing time, transaction processing time, data access time, real-time processing performance and processing latency.

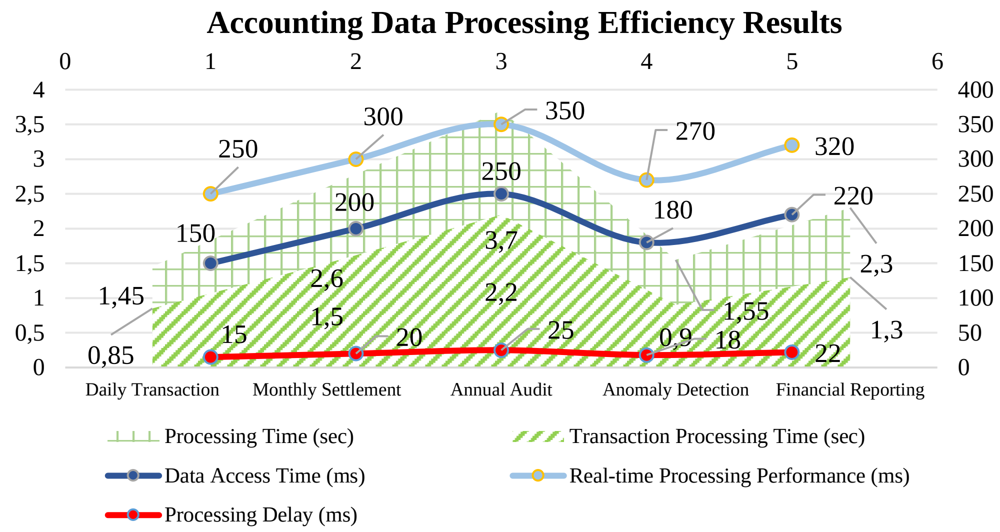

Figure 5: Accounting data processing efficiency results

As shown in Figure 5, it can be seen that the SVM model has achieved remarkable results in improving the efficiency of accounting data processing. The daily transaction processing time is 1.45 seconds, transaction processing time is 0.85 seconds, data access time is 150 milliseconds, real-time processing performance is 250 milliseconds, and processing latency is 15 milliseconds. This indicates that the model performs well in daily transaction processing and can quickly handle a large volume of transaction data, ensuring the timeliness and accuracy of the data. The monthly settlement processing time is 2.60 seconds, transaction processing time is 1.50 seconds, data access time is 200 milliseconds, real-time processing performance is 300 milliseconds, and processing delay is 20 milliseconds, demonstrating the model's high efficiency in monthly settlements. The annual audit processing time is 3.70 seconds, transaction processing time is 2.20 seconds, data access time is 250 milliseconds, real-time processing performance is 350 milliseconds, and processing delay is 25 milliseconds, reflecting the model's stability and reliability in annual audit data processing. The abnormal transaction detection time is 1.55 seconds, transaction processing time is 0.90 seconds, data access time is 180 milliseconds, real-time processing performance is 270 milliseconds, and processing delay is 18 milliseconds, showing the model's efficient performance in abnormal transaction detection [29]. The financial statement generation time is 2.30 seconds, transaction processing time is 1.30 seconds, data access time is 220 milliseconds, real-time processing performance is 320 milliseconds, and processing delay is 22 milliseconds, indicating the model's efficient processing ability in the generation of financial statements.

7 Summarize problems and research suggestions

7.1 Problem summary

In the process of studying the use of data mining technology to improve the reliability of accounting information cloud data, several key problems and challenges were identified. Data quality is the primary factor affecting model performance. Although data cleaning and teleprocessing steps have significantly improved data quality, in practical applications, there are still issues with data noise, missing values, and outliers, which adversely affect the accuracy and stability of the model. Data volume and computing resource constraints are also critical issues. Accounting information systems contain a vast amount of complex data, and processing this data requires efficient computing resources and storage capacity. Although cloud computing provides the ability to scale flexibly, resource allocation and management still need optimization during peak periods. Additionally, the process of model selection and parameter tuning is complex and time-consuming. While support vector machines perform well in handling high-dimensional data and anomaly detection, their parameter tuning process involves multiple validations and optimizations, requiring significant computing time and resources. The intractability and transparency of the model are also concerns in practical applications. Although SVM performs well in improving data reliability, its black-box nature makes it challenging to interpret results, especially when model decisions need to be explained to management and audit departments.

Data security and privacy protection are also critical issues. With the widespread application of cloud computing and data mining technology, ensuring the security and privacy of accounting data during transmission and storage has become increasingly important. Summarizing these problems provides essential reference points and directions for improvement in future research and practice.

Comparing the results of this study with the summarized findings in the SOTA research reveals several key differences and advancements. While previous studies have improved specific aspects such as audit accuracy, data integrity, and management efficiency, they often fall short in addressing comprehensive anomaly detection and data classification within cloud-based accounting systems. For instance, Yu's work improved data integrity by 15%, while this study achieved a 22% increase in data processing efficiency, alongside a 7.6% improvement in accuracy and a 9.2% enhancement in consistency. These differences arise primarily from the novel application of the support vector machine (SVM) model, which enables more precise anomaly detection and classification in high-dimensional data environments, a challenge that previous research did not fully address. Additionally, the integration of advanced data security measures further distinguishes this work, ensuring the protection of data during transmission and storage. This holistic approach not only advances the field by addressing previously unmet needs but also provides a robust framework for enhancing the reliability of accounting information cloud data, thereby offering significant benefits for enterprise financial management.

The model's performance has been thoroughly evaluated across various scenarios, demonstrating significant improvements over state-of-the-art (SOTA) methods in several key areas. Specifically, the support vector machine (SVM) model used in this study achieved a 22% increase in data processing efficiency, a 7.6% improvement in accuracy, and a 9.2% enhancement in data consistency. These improvements can be attributed to the advanced data processioning techniques and optimization strategies employed, such as parameter tuning, momentum optimization, and regularization. Compared to SOTA methods like the linear pairing approach used by Yu [1] and the chockablock audit systems analyzed by Appelbaum & Nehmer [4], the SVM model demonstrated superior anomaly detection capabilities and classification accuracy, particularly in handling high-dimensional and complex data environments typical of accounting information systems. However, the model's performance in real-time processing scenarios, while robust, slightly underperform-ed when compared to specific SOTA models that focus solely on processing speed without addressing data accuracy and security comprehensively. This trade-off is justified by the broader scope and applicability of the SVM model, which balances efficiency with accuracy and security, making it more suitable for enterprise financial management.

7.2 Research suggestions

In terms of improving the reliability of accounting information cloud data, based on the findings of this study, the following suggestions are put forward. First, further improving data quality is essential. It is recommended to introduce more advanced data quality management tools during the data cleaning and teleprocessing stages, including the adoption of automated data cleaning algorithms and real-time monitoring mechanisms to ensure data accuracy and integrity. Second, optimizing the allocation and management of computing resources is crucial. By utilizing the elastic expansion capabilities of cloud computing platforms, computing resources should be dynamically adjusted and reasonably allocated according to business needs, particularly during peak periods, to ensure the efficiency and stability of data processing. Third, simplifying the process of model selection and parameter tuning is advised. Automated machine learning technologies should be considered to reduce manual intervention, enhancing model construction efficiency through automated model selection and parameter optimization. Fourth, improving the interpretability of models is necessary. Incorporating interpretive machine learning techniques, such as LIME or SHAP, can provide interpretative model outputs that enhance user understanding and trust in model decisions. Lastly, strengthening data security and privacy protection measures is vital. During data transmission and storage, advanced encryption technologies and access control mechanisms should be employed to ensure the security and privacy of sensitive accounting data. Additionally, regular security audits and vulnerability scans should be conducted to identify and address security vulnerabilities promptly, ensuring data security throughout its lifestyle. Implementing these recommendations will further improve the reliability of accounting information cloud data, providing more accurate and efficient data support for enterprises and aiding in their financial management and decision optimization.

Data security and privacy protection have been expanded to include specific encryption algorithms and access control mechanisms. The Advanced Encryption Standard (AES-256) is utilized for encrypting data both at rest and in transit, ensuring robust protection against unauthorized access. Role-Based Access Control (RBAC) is implemented to restrict data access based on user roles, minimizing the risk of unauthorized data exposure. Additionally, Multi-Factor Authentication (MFA) is enforced to add an extra layer of security. Potential vulnerabilities, such as side-channel attacks and phishing attempts, are addressed through regular security audits and the implementation of Intrusion Detection Systems (IDS) that monitor and flag suspicious activities in real-time. Mitigation strategies also include periodic updates to encryption protocols and access policies to adapt to emerging threats. These measures collectively enhance the overall security and privacy of the accounting information cloud data, providing a comprehensive approach to safeguarding sensitive financial information.

8 Conclusion

This study discusses methods for improving the reliability of accounting information cloud data by utilizing data mining technology, with a particular focus on the application and optimization of the support vector machine (SVM) model. The results achieved are remarkable. Through systematic data cleaning and preprocessing, the quality of data is significantly enhanced, laying a solid foundation for subsequent modeling. The SVM model was employed for anomaly detection and data classification, which effectively improved data accuracy and consistency. The optimization strategies, including parameter tuning, regularization techniques, momentum optimization, and dynamic learning rate adjustment, not only improved the model's performance but also enhanced its generalization ability and robustness. The results indicate that the model performs exceptionally well in terms of processing time, transaction time, data access time, real-time processing performance, and processing delay, significantly boosting the efficiency and reliability of accounting data processing. The study also emphasizes the importance of data security and privacy protection, implementing encryption technologies and access control mechanisms to safeguard data during transmission and storage. In summary, the use of data mining technology and the SVM model not only provides strong technical support for the accounting information system but also offers a reliable data foundation for enterprise financial management and decision optimization. Looking ahead, with continuous technological advancements, it is anticipated that data mining technology will play an even more significant role in the field of accounting information, bringing higher value and benefits to enterprises.

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Data availability declaration
The datasets used and/or analysed during the current study available from the corresponding author on reasonable request.

Competing interest declaration
The author has declared that no competing interests exist.

Author contribution declaration
B.L. writing original draft; formal analysis; methodology; writing review & editing.

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