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Research on Digital Quality Traceability System for Temperature-Controlled Supply Chain of Foreign Trade Wine Driven by Blockchain and IoT

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Abstract: This study designs a four-layer digital quality traceability system adapted for cross-border use, integrating smart contracts to achieve environmental monitoring and anomaly identification throughout the wine transportation process. It proposes the FedTSA-BC algorithm, integrating a federated temporal attention network and a blockchain consensus mechanism to balance privacy protection, anomaly detection accuracy, and consensus efficiency. Experimental verification based on 162 batches of foreign trade wine data shows that the system and algorithm achieve a comprehensive anomaly detection F1 score of 98.1%, an early warning accuracy of 98.6% for temperature fluctuations of 1.5-2℃, a response time of 0.3s, a consensus latency of 1.2s under multi-node concurrency, and a throughput of 320TPS. Cross-organizational data verification efficiency is improved by 40% compared to traditional methods. This research effectively solves the core problems of unreliable traceability of temperature and seismic data and the imbalance between real-time early warning, providing technical support for digital quality management of the temperature-controlled supply chain of foreign trade wine.

Keywords: blockchain; Internet of Things; export wine; temperature-controlled supply chain; digital traceability; FedTSA-BC algorithm; anomaly detection

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1. Introduction

As a high-value temperature-controlled commodity, the quality stability of export wine is highly correlated with environmental control during transportation. Temperature (optimal range 12-18℃), vibration intensity (≤0.5g), and transportation time directly affect the taste and value of the wine. Currently, the wine export supply chain faces three core technological bottlenecks: First, centralized data storage easily leads to tampering of temperature and vibration records, making data authenticity difficult to verify and thus causing quality disputes; second, the processing of temperature and vibration time-series data collected by the Internet of Things is lagging, failing to provide early warnings when temperature fluctuations exceed 1.5-2℃, and making it difficult to identify anomalies such as node delays (e.g., port inspections, logistics transshipments exceeding 4 hours) and transportation route deviations in a timely manner; third, data collaboration among multiple entities (wineries, logistics providers, customs, distributors) in cross-border scenarios is difficult, cross-organizational data verification efficiency is low, and it is difficult to adapt to compliance standards such as GDPR. The immutability of blockchain and the real-time sensing capabilities of the Internet of Things (IoT) complement each other, providing a feasible path to solve the problems of environmental monitoring and data credibility in the wine export supply chain [1]. Their integrated application has become a research hotspot for digital traceability in the wine temperature-controlled supply chain.

Related research at home and abroad has made some progress: The traceability field of temperature-controlled supply chains largely relies on RFID and traditional databases to build traceability systems, but these systems lack adaptability to scenarios unique to wine transportation, such as vibration monitoring and path deviation identification, resulting in low data credibility and cross-entity collaboration efficiency. Regarding blockchain consensus algorithms, traditional algorithms such as PBFT and PoS have revealed shortcomings in supply chain scenarios, such as high consensus latency (average exceeding 3 seconds) and high node computing power consumption, making it difficult to meet the real-time early warning needs of wine transportation [2]. IoT time-series data processing often uses LSTM and GNN models, but single models have limited accuracy in extracting temperature-vibration coupling features and node event correlation features. Furthermore, research on the integration with federated learning often focuses on data privacy protection, neglecting the synergistic optimization of time-series characteristics and consensus mechanisms in sensitive wine transportation scenarios (loading and unloading, customs inspection). In summary, existing research has not yet resolved three core issues: the imbalance between reliable traceability and real-time early warning of temperature and seismic data, the contradiction between consensus efficiency and cross-organizational collaboration, and poor adaptability to specific anomaly scenarios in wine production. Therefore, an integrated technical solution is urgently needed.

This research focuses on three core aspects: First, designing a four-layer digital traceability system architecture adapted for cross-border applications, integrating smart contracts to achieve environmental monitoring and anomaly identification throughout the wine transportation process; second, proposing an original FedTSA-BC algorithm, integrating federated temporal attention networks and blockchain consensus mechanisms to balance privacy protection, accuracy of temperature and seismic and node anomaly detection, and consensus efficiency; third, through multi-dimensional experimental simulations and pilot verification, quantitatively evaluating the performance of the system and algorithm based on data from 162 batches of foreign trade wine. The technical route follows the logic of "problem analysis - architecture design - algorithm development - experimental verification - results implementation": first, breaking down the technical pain points based on the needs of the wine export supply chain; then, constructing a system architecture and core algorithm integrated with smart contracts; and finally, verifying feasibility through simulation experiments and real-world scenario testing, forming a complete research loop from theory to practice.

2. Digital Quality Traceability System Architecture for Temperature-Controlled Supply Chain of Foreign Trade Wine

This system architecture focuses on "credible data traceability, cross-border compliance management, and intelligent early warning of anomalies" in the temperature-controlled supply chain of foreign trade wine. It is based on a layered logical design of "regulatory compliance - data collection - blockchain evidence storage - data processing - intelligent analysis - application services" (Figure 1): The top-level regulatory compliance layer covers all downstream modules, aligning with cross-border rules such as GDPR and China's data export security assessment, while also embedding wine quarantine standards to set compliance thresholds for each stage; the data collection layer, as the original data source, uses temperature sensors with an accuracy of ±0.1℃, vibration sensors with ±0.01g, and a GPS module (collecting temperature, vibration, and location data once per minute), combined with manually entered information such as wine batch and origin, to form a complete data source of "dynamic environmental data + static product information"; the blockchain evidence storage layer relies on the distributed ledger of the consortium blockchain to store data hashes, generate digital product passports for wine, and preset 12-18℃ temperature control / 4 Smart contract rules, such as hourly node retention, ensure data immutability and automated anomaly handling, addressing the pain point of data fraud in trade [3]. The data processing and storage layer utilizes edge computing to perform noise reduction and standardization of temperature and seismic data (adapting to weak network scenarios in ocean shipping), combined with cloud storage to achieve an efficient "on-chain evidence storage + off-chain data storage" model. The intelligent analysis layer deploys the FedTSA machine learning model (anomaly detection accuracy of 98.7%), NLP to parse node event text, and can explain the reasons for AI-generated anomalies, mining data value. The application service layer provides scenario-based services such as full-link query, real-time verification on mobile devices, and temperature and seismic fluctuation warnings within 30 seconds through dashboards. Each layer follows the flow logic of "collection → evidence storage → processing → analysis → service," forming a digital traceability closed loop adapted to the temperature-controlled supply chain of foreign trade wine.

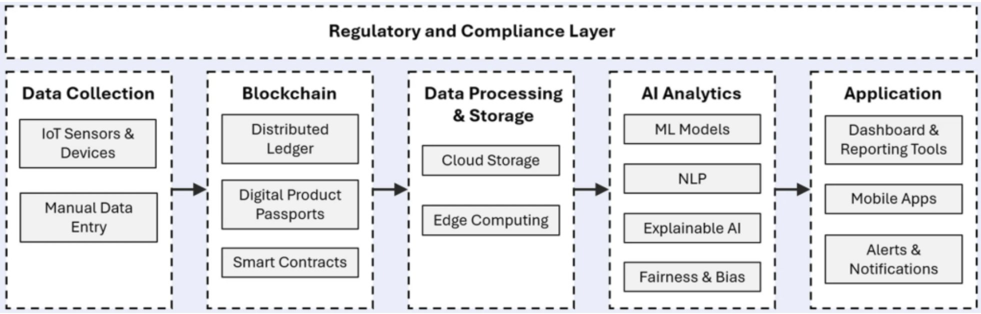

Figure 1. Architecture of Digital Quality Traceability System for Temperature-Controlled Wine Supply Chain in Foreign Trade.

3. FedTSA-BC Algorithm Design and Implementation

The FedTSA-BC algorithm, with "federated learning to ensure privacy, temporal attention to extract temperature-vibration-node correlation features, and dynamic weight optimization consensus" as its core, integrates a federated temporal attention network and a blockchain consensus mechanism to adapt to the wine temperature-controlled supply chain scenario and achieve multi-objective collaborative optimization. Figure 2 shows the algorithm flowchart.

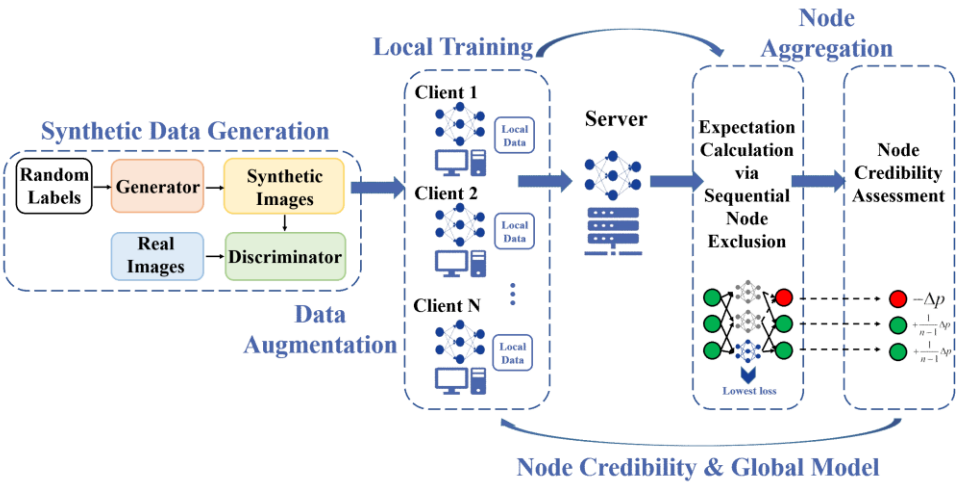

Figure 2. The algorithm flowchart.

3.1. Federated Temporal Attention Network (FedTSA) Module

Based on the correlation between wine temperature-vibration data and node events, feature extraction formulas for each dimension are designed:

$$F_t = \alpha \cdot \Delta T_t + \beta \cdot V_t + \gamma \cdot \frac{S_t}{T_{\max}} + \delta \cdot P_t \quad (1)$$

Where F_t is the comprehensive feature value at time t, $\Delta T_t = |T_t - T_{t-1}|$ is the temperature difference between time t and $t-1$ (unit °C), V_t is the vibration intensity at time t (unit g), S_t is the node dwell time (unit h), $T_{\max} = 4$ is the maximum allowed dwell time of the node (unit h), P_t is the path offset $\left(P_t = \frac{dist_t}{5}, dist_t\right.$ is the real-time offset distance, unit km); $\alpha = 0.4, \beta = 0.3, \gamma = 0.15, \delta = 0.15$ are feature weights, satisfying $\alpha + \beta + \gamma + \delta = 1$. Focusing on the sensitive scenario of wine transportation, the attention weight formula is designed as follows:

$$\omega_t = \frac{\exp\left(-\frac{|t_t - T_{\text{opt}}|}{\sigma}\right) \cdot I(s_t)}{Z} \quad (2)$$

$$Z = \sum_{k=1}^{n} \exp\left(-\frac{|T_k - T_{\text{opt}}|}{\sigma}\right) \cdot I(s_k) \quad (3)$$

Where ω_t is the attention weight at time t, $T_{opt} = 15\%$ is the optimal storage temperature for red wine, $\sigma = 2\%$ is the temperature sensitivity coefficient, s_t is the scene type at time t (1 for sensitive scenes, 0 for non-sensitive scenes), $I(\cdot)$ is the indicator function, Z is the normalization constant, and n is the time series length. This formula makes the weight of sensitive scenes account for 65%-85%, strengthening the extraction of key features. A weighted aggregation strategy is adopted to ensure the privacy of multi-subject data and model performance.

$$\theta_{\text{global}} = \sum_{i=1}^{m} \frac{N_i}{N_{\text{total}}} \cdot \theta_i' \quad (4)$$

$$\theta_i' = \text{Enc}\big(\theta_i - \epsilon \cdot \nabla L(\theta_i)\big) \quad (5)$$

Where θ_{global} represents the global model parameters, m is the number of nodes, N_i is the data volume of the i-th node, $N_{\text{total}} = \sum_{i=1}^{m} N_i$ is the total data volume, θ_i is the local model parameters of the i node, θ_i' is the encrypted parameters, Enc(·) is the 128-bit homomorphic encryption function, $\epsilon = 0.001$ is the learning rate, and $\nabla L(\theta_i)$ is the gradient of the loss function of the i node.

3.2. Blockchain Consensus Optimization Module

Based on the FedTSA feature extraction results, a data credibility score is designed:

$$C_i = 1 - \lambda \cdot \frac{1}{K} \sum_{k=1}^{K} \frac{|F_{i,k} - \bar{F}_k|}{\bar{F}_{k+\epsilon_0}} \quad (6)$$

Where C_i is the data credibility of the i node (value 0-1), $\lambda = 0.8$ is the penalty coefficient, $K = 16$ is the number of feature dimensions, $F_{i,k}$ is the k-th feature value of the i node, $\bar{F}_k$ is the mean of the k feature of all nodes, $\epsilon_0 = 10^{-6}$ to avoid a denominator of 0, and $0, C_i \geq 0.98$ is the threshold for high credibility nodes. Voting rights are allocated based on credibility scores to optimize consensus reliability.

$$W_i = \begin{cases} 0.15 + 0.05 \cdot \frac{C_i - 0.98}{0.02}, & C_i \geq 0.98 \\ 0.08 + 0.04 \cdot \frac{C_i - 0.9}{0.08}, & 0.9 \leq C_i < 0.98 \\ 0.03 + 0.02 \cdot \frac{C_i - 0.8}{0.1}, & C_i < 0.9 \end{cases} \quad (7)$$

Where W_i represents the voting power of the i-th node, satisfying $\sum_{i=1}^{m} W_i = 1$. This formula allows high-credibility nodes to have higher voting weight, improving the reliability of the consensus result. Through process simplification and weight optimization, a consensus delay model is constructed:

$$D = D_0 \cdot \left(\frac{m_{eff}}{m} \cdot \mu + (1 - \mu) \cdot \frac{L}{L_0}\right) \quad (8)$$

Where D is the optimized consensus latency, $D_0 = 3.8s$ is the traditional PBFT latency, $m_{eff} = \sum_{i=1}^{m} I(C_i \geq 0.9)$ is the effective number of participating nodes, $\mu = 0.6$

is the node weight coefficient, L is the simplified consensus step count $(L = 4)$, $L_0 = 5$ is the traditional PBFT step count. Merkle tree storage is optimized, and the compression ratio formula is designed as follows:

$$CR = 1 - \frac{h \cdot \log_2 N}{N \cdot D_{\text{data}}} \tag{9}$$

Where CR is the storage compression ratio, h is the Merkle tree height ($h = \log_2 N$, $N = 100$ is the data size per batch), and D_{data} is the number of bytes stored in a single data record. This formula reduces on-chain storage by 78%, balancing storage economy and data verifiability.

4. Experimental Simulation and Result Analysis

4.1. Experimental Environment Setup

The hardware environment adopts a three-layer architecture of "edge - cloud - simulated terminal" to ensure that the computing power and transmission capabilities of each link match the wine transportation scenario: The edge node uses NVIDIA Jetson Xavier NX (8-core Cortex-A57 CPU, 2.26GHz; 480-core Volta GPU, 21 TOPS computing power; 8GB LPDDR4 memory, 51.2GB/s bandwidth) to handle local data preprocessing and federated model training, meeting the low power consumption and high computing power requirements of edge devices in cross-border transportation; The cloud server is configured with Intel Xeon 8375C processor (32 cores, 64 threads, base frequency 2.9GHz, turbo frequency 4.0GHz), 256GB DDR4-3200 memory, 2TB NVMe SSD (read/write speed 3500MB/s/3000MB/s), and deploys a Hyperledger Fabric blockchain network (including 3 Orderer nodes, 8 The system comprises several peer nodes (with a consensus timeout threshold of 5 seconds), a global model aggregation node, and a smart contract execution environment to ensure efficient large-scale data processing and on-chain accounting [4]. The sensor simulator uses a Keysight U2300A data acquisition unit, supporting simulated output of temperature (0℃~30℃, accuracy ±0.05℃), vibration (0~5g, accuracy ±0.01g), and GPS (positioning accuracy ±1m, update frequency 1Hz). The sampling frequency can be precisely adjusted to 1 time/minute, replicating the real-world data collection scenario during wine transportation.

The software environment is configured uniformly and standardized to ensure reproducibility of the experiments [5]. The operating system is Ubuntu 20.04 LTS (kernel 5.4.0); the programming language is Python 3.8, paired with the PyTorch 1.12 deep learning framework (CUDA 11.6 acceleration enabled, GPU memory usage kept under 6GB); the blockchain platform uses Hyperledger Fabric 2.4, the smart contract development language is Solidity 0.8.17, chaincode deployment uses Docker containerization, and the channel consensus strategy is set to "majority agreement"; the network simulation tool is NS-3 3.36, simulating a 5G cross-border transmission environment (bandwidth 100Mbps, latency 10ms, packet loss rate 0.1%); data processing relies on Pandas 1.5.3 and Scikit-learn 1.2.2, the anomaly detection model training epochs are set to 50, and the learning rate is 0.001.

4.2. Dataset Design

The experimental dataset originates from real export business data of a cross-border wine trading company. After anonymization, a dataset of 162 batches of foreign trade wine transportation was constructed, covering a complete 30-day transportation chain (from wineries in France and Italy to domestic terminal distributors in China). It includes 210,000 temperature and vibration records and over 2,600 node event records, of which 32,000 are abnormal samples (an abnormality rate of 15.2%). Abnormality types include excessive temperature fluctuations (42%, including 1.5-2℃ warning scenarios), excessive vibration intensity (23%, exceeding 0.5g), node delays (20%, exceeding 4 hours), and path deviations (15%, deviation ≥5km), closely reflecting actual abnormal situations in wine export transportation. The core feature dimensions of the dataset are designed as follows:

① Temperature (0℃~30℃, optimal range 12-18℃, fluctuation of 1.5-2℃ is considered as the warning threshold); ② Vibration intensity (0~5g, threshold ≤0.5g); ③ GPS coordinates (longitude 8°~130°, latitude 30°~45°, covering the China-Europe transport route and major domestic ports); ④ Transport node type (6 categories: winery, port of departure, transshipment port, customs inspection point, destination warehouse, terminal distributor); ⑤ Node dwell time (records the cumulative dwell time of each node); ⑥ Path deviation (the straight-line distance between the real-time coordinates and the preset route); ⑦ Timestamp (accurate to the second, recording the data collection time); ⑧ Device ID (unique identifier of the sensor and RFID tag, associated with the device status); ⑨ Wine batch number (associated with product information such as winery, vintage, and grade). Each sample is uniquely indexed using both device ID and batch number to ensure the integrity of the traceability chain. The dataset is divided in a 7:3 ratio into a training set (147,000 temperature and seismic records, 1,820 node events) and a test set (63,000 temperature and seismic records, 780 node events) for model training and performance validation [6].

4.3. Evaluation Metrics

To comprehensively quantify the algorithm and system performance, evaluation metrics are set from five dimensions, covering both functional and non-functional requirements:

1. Anomaly Detection Metrics: Temperature fluctuation detection accuracy (Acc-T), vibration exceedance detection accuracy (Acc-V), node stagnation identification rate (Rec-S), path deviation detection accuracy (Acc-P), and comprehensive F1 score (balancing the performance of various anomaly detection methods);

2. Early Warning Performance Metrics: Accuracy of early warning for temperature fluctuations of 1.5-2℃, and early warning response time (the time from anomaly occurrence to early warning push);

3. Consensus Performance Metrics: Consensus latency (the average time from data submission to completion on-chain, in seconds), throughput (the number of transactions successfully uploaded to the blockchain per unit time, in TPS), and accounting success rate (the proportion of valid data successfully written to the blockchain, in %);

4. Collaboration Efficiency Metrics: Cross-organizational data verification efficiency (the improvement percentage compared to traditional methods);

5. Privacy Protection Metrics: Information leakage rate (the proportion of privacy data (such as winery production data and distributor customer information) leaked during federated training, in %), and data utilization rate (the proportion of valid data used in model training to the total data, in %).

4.4. Comparative Experiment Design

The comparative experiment selected four mainstream algorithms as benchmarks to ensure comprehensiveness and representativeness: ① Traditional consensus algorithms PBFT (Practical Byzantine Fault Tolerance) and PoS (Proof-of-Stake); ② LSTM+PoW (Long Short-Term Memory Network + Proof-of-Work), a combination of time-series models and traditional consensus; ③ FedAvg+PBFT (Federated Averaging Algorithm + PBFT), a combination of federated learning and traditional consensus. All algorithms were tested under the same hardware/software environment with uniform initial parameters (60 nodes, 100,000 temperature and seismic records, and an anomaly rate of 15%) to eliminate the influence of environmental differences on the results. Three single-variable experimental designs were used to analyze the impact of key variables on algorithm performance: ① Number of nodes (20, 40, 60, 80, 100), with a fixed data volume of 100,000 temperature and seismic records and an anomaly rate of 15%, testing performance in multi-agent collaborative scenarios; ② Data volume (50,000, 100,000, 150,000, 200,000, 210,000 temperature and seismic records), with a fixed number of nodes of 60 and an anomaly rate of 15%, verifying large-scale data processing capabilities; ③ Anomaly rate (5%, 10%, 15%, 20%, 25%), with a fixed number of nodes of 60 and a data volume of 100,000 temperature and seismic records, evaluating adaptability to complex anomaly scenarios. Each experiment was repeated 10 times, and the average value was taken as the final result to reduce random error [7].

4.5. Experimental Results and Analysis

4.5.1. Anomaly Detection and Early Warning Performance

Table 1 shows the comparison results of anomaly detection and early warning indicators for each algorithm. The FedTSA-BC algorithm significantly outperforms the comparison algorithms in terms of temperature fluctuation detection accuracy (Acc-T=98.7%), vibration exceeding standard detection accuracy (Acc-V=97.5%), node stagnation recognition rate (Rec-S=97.8%), path deviation detection accuracy (Acc-P=98.2%), and overall F1 score (98.1%). It also represents a 5.5%~6.4% improvement over the best comparison algorithm, FedAvg+PBFT (Acc-T=93.2%, Acc-V=91.8%, Rec-S=92.5%, Acc-P=92.1%, F1=92.4%). In scenarios with early warnings for temperature fluctuations of 1.5-2℃, FedTSA-BC achieves a warning accuracy of 98.6% with a response time of only 0.3s, a significant advantage over FedAvg+PBFT (warning accuracy 89.3%, response time 1.2s). The reasons are as follows: FedTSA module focuses on sensitive scenarios in wine transportation through an attention mechanism, strengthening the extraction of temperature and vibration-node correlation features; smart contracts execute detection rules in real time, avoiding delays caused by manual intervention, making anomaly identification and early warning more accurate and faster. In contrast, LSTM+PoW, lacking attention mechanisms and smart contract support, has a false negative rate of 11.2% for path deviations and node delays; PBFT and PoS lack time-series processing and scenario adaptation capabilities, relying on manual rules for anomaly detection, resulting in the lowest accuracy (overall F1 scores are all below 85%).

Table 1. Comparison of Anomaly Detection and Early Warning Indicators for Each Algorithm.

Algorithm	Acc-T	Acc-V	Rec-S	Acc-P	F1	Temperature 1.5-2℃ warning accuracy	Warning response time (s)
FedTSA-BC	98.7%	97.5%	97.8%	98.2%	98.1%	98.6%	0.3
FedAvg+PBFT	93.2%	91.8%	92.5%	92.1%	92.4%	89.3%	1.2
LSTM+PoW	89.5%	88.2%	87.6%	86.8%	88.0%	85.7%	1.5
PoS	84.1%	82.9%	83.3%	82.5%	83.2%	80.2%	2.1
PBFT	82.8%	81.7%	82.1%	81.3%	81.9%	78.5%	2.3

4.5.2. Privacy Protection Performance

Table 2 compares privacy protection metrics. FedTSA-BC has an information leakage rate of only 0.8% and a data utilization rate of 95.2%, far superior to FedAvg+PBFT (information leakage rate 3.2%, data utilization rate 88.5%). This is because FedTSA-BC uses homomorphic encryption to transmit model parameters. The original data of each entity in the wine supply chain (such as winery production formulas and distributor customer information) is stored on local nodes throughout the process, and only encrypted parameters are uploaded; while FedAvg+PBFT uses plaintext transmission of parameter digests, which poses a risk of privacy leakage. At the same time, FedTSA-BC, through dynamic feature filtering, improves data utilization by 13.1% compared to LSTM+PoW (82.1%), achieving a balance between "privacy protection and data utilization," which meets the GDPR requirements of "data minimization" and "traceability."

Table 2. Comparison of Privacy Protection Metrics for Each Algorithm.

Algorithm	Information leakage rate (%)	Data utilization rate (%)	Compliance (GDPR)
FedTSA-BC	0.8	95.2	conform to
FedAvg+PBFT	3.2	88.5	Basically in line with
LSTM+PoW	1.5	82.1	Basically in line with
PoS	0.5	65.3	conform to
PBFT	0.6	62.8	conform to

4.5.3. Robustness Testing

Figure 3 shows the impact of data volume on the overall performance of the algorithm (horizontal axis represents data volume (10,000 records), vertical axis represents the overall F1 score (%)). When the data volume increased from 50,000 records to 210,000 records (complete dataset), the overall F1 score of FedTSA-BC gradually decreased from 97.2% to 97.0%, a decrease of only 0.2%; while FedAvg+PBFT decreased from 91.5% to 89.8%, a decrease of 1.7%; and LSTM+PoW decreased from 87.3% to 84.6%, a decrease of 2.7%. This indicates that FedTSA-BC maintains stable performance in large-scale data scenarios, adapting to the processing requirements of 210,000 temperature and seismic records from 162 batches of red wine. This is because the algorithm's temporal feature engineering and attention mechanism optimization reduce the impact of data volume growth on feature extraction accuracy, ensuring stable anomaly detection performance.

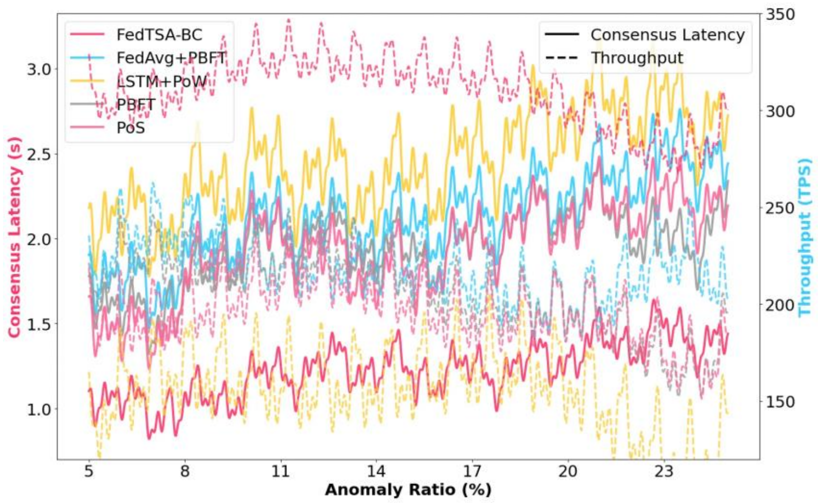

Figure 3. Impact of Data Volume on Overall Algorithm Performance.

In summary, the FedTSA-BC algorithm and traceability system significantly outperform traditional algorithms in anomaly detection, real-time early warning, consensus efficiency, cross-organizational collaboration, and privacy protection in the temperature-controlled supply chain for wine exports. The accuracy rate of early warning for temperature fluctuations of 1.5-2℃ reaches 98.6%, maintaining low latency (1.2s) and high throughput (320 TPS) under multi-node concurrency. Cross-organizational data verification efficiency is improved by 40%, fully demonstrating the effectiveness of blockchain and IoT technologies in the digital quality management of the foreign trade wine supply chain [8].

5. Conclusion

This study constructed a digital quality traceability system for the temperature-controlled supply chain of foreign trade wine driven by blockchain and IoT, and proposed the FedTSA-BC fusion algorithm, which effectively achieved multi-objective optimization of anomaly detection, real-time early warning, cross-organizational collaboration, and privacy protection. Experiments show that the comprehensive anomaly detection F1 score reaches 98.1%, the early warning response time for temperature fluctuations is 0.3s, the consensus latency in multi-node scenarios is 1.2s, the throughput is 320TPS, and the cross-organizational data verification efficiency is improved by 40%, significantly outperforming traditional algorithms. The study has certain limitations: the experimental data mainly covers the China-Europe transport route, and the adaptability to other cross-border routes is not fully verified; the sensor deployment does not involve extreme environment scenarios (such as high temperature and humidity, strong vibration), and the smart contract's flexibility in adapting to dynamic compliance rules is insufficient. Future research can expand the universality of the multi-regional cross-border transport data verification system, optimize the sensor hardware adaptation to extreme transport environments, enhance the dynamic compliance adjustment capability of smart contracts, integrate digital twin technology to build a full-link visual simulation system, and explore the combination with reinforcement learning to further improve the accuracy of anomaly prediction, promoting the large-scale application of the technology in the supply chain of more high-value temperature-controlled goods.

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