
Streamlining warehouse efficiency: A smart contract approach to blockchain and machine learning integration

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Abstract.

The combination of blockchain technology and machine learning (ML) has the ability to optimize warehouse management systems (WMS) by improving efficiency, transparency, and security. This research explores blockchain's decentralized, immutable, and transparent ledger, visualizing ML algorithms to improve various aspects of warehouse operations. Blockchain ensures secure and tamper-proof record-keeping, which enhances the reliability of data used for training ML models, while ML provides advanced predictive analytics and real-time decision-making capabilities. The synergy of such technologies addresses key challenges in WMS, including reducing errors, enhancing the accuracy, and automating tasks. This paper proposes a framework for integrating blockchain and ML in WMS, discusses the technical architecture, and evaluates the performance improvements in terms of operational efficiency and security. The application of advanced Long-Short Term Memory (LSTM) networks on data generated using Amazon sales data processed using Probability Density grouping achieved a Pearson Correlation of 0.9908 and RMSE of 0.0200. Our findings demonstrate that the hybrid approach not only streamlines warehouse processes but also fosters trust and collaboration across supply chain stakeholders.

Keywords. Blockchain Technology; Machine Learning; Warehouse Management Systems; Smart Contracts; Supply Chain Management.

1. INTRODUCTION

Supply chain management controls the management of products and services from raw material sourcing to final product handover. It consists of managing the movement, storage, and inventory at each stage of production, as well as coordinating suppliers to make sure smooth transitions from source to destination. This process includes handling work-in-progress and completed goods, forming a network of suppliers to facilitate efficient order fulfillment. Warehouses are crucial to the supply chain, providing not only as storage facilities but also as key points for shipping and receiving goods. As warehouse operations grow more complex, the use of technology, particularly machine learning algorithms, is becoming essential for improving efficiency, reducing costs, and boosting productivity.[1][2][3]

Machine learning enables the discovery of patterns in the supply chain by using algorithms to analyze performance and identify areas for improvement more efficiently than manual methods. It significantly impacts inventory levels, quality, supply and demand, production planning, and transport management, especially in warehouse management.[4]

Blockchain technology improves transparency and accuracy in end-to-end supply chain tracking by digitizing physical assets and providing a decentral-ized, immutable record of transactions. This allows organizations to track assets from production to final delivery or use, providing greater visibility for both businesses and consumers. For high-value items like diamonds and pharmaceutical drugs, blockchain re-duces fraud by enabling companies to trace the flow of ingredients and products through subcontractors, minimizing losses from counterfeit and gray market activities while boosting consumer confidence in the authenticity of goods. Blockchain, as a decentralized distributed ledger, abolish the need for a central au-thority or administrator for managing data records and transactions.[5][6] Every block in the blockchain contains a cryptographic hash linking it to the earlier block, ensuring the immutability of the entire chain.

When integrated with the Internet of Things (IoT), blockchain can enhance logistics by enabling faster deliveries and reducing operational costs across various applications.[7][8] By introducing au-tonomy and transparency into logistics processes, blockchain improves both security and operational efficiency.[9][10]

Emerging technologies like Distributed Ledger Technology (DLT) and IoT offer solutions for ad-dressing challenges related to tracking and prove-nance in supply chains.

Predictive data analytics employs current and histor-ical data to forecast future events or unknown out-comes. By analyzing this data, it allows for the as-sessment of the likelihood of specific situations or occurrences.[11-13] Unlike general forecasting, pre-dictive data analytics provides insights at the indi-vidual level—pertaining to specific customers, employees, or systems.

Smart contracts are self-executing, immutable, and distributed code deployed on the blockchain, written in Solidity.[14][15] They are tamper-proof and validated by everyone on the network, ensuring secure and transparent transactions. Once deployed, smart contracts cannot be altered, allowing them to govern transactions and decision-making processes. These contracts enable the transparent transfer of as-sets—such as money, shares, or property—without intermediaries. Like traditional contracts, they define rules and penalties, but smart contracts automatically enforce the agreed conditions.

Remaining paper is organized as follows. Section II discusses the ongoing research scenario of the supply chain. Section III throws light on the various processes involved in the development of smart WMS. Section IV demonstrates the implementation part along with dataset used and results developed. Finally Section V concludes the paper.

demands without considering the data volume. Taking into consideration this ratio, green IT technologies have important benefits in terms of:

2. RELATED WORK

Z. Ren et. al. [17] explores how integrating digital twin technology with machine learning enhances the full life cycle management of complex equipment, crucial for modern manufacturing's intelligent trans-formation. It proposes a system embedding machine learning into digital twins and constructs a life cycle digital twin for complex equipment. Experimental results show that abnormal axle temperatures can be detected a week in advance, demonstrating the method's effectiveness.

Safak Kayikci et. al. [1] reviews the contributions of machine learning and blockchain integration, including enhanced security, privacy, and decentralization. Blockchain ensures reliable, tamper-proof decentralized record-keeping, whereas machine learning provides the capability to extract meaningful insights from large-scale data. Together, these technologies promise to reshape industries by streamlining operations, fostering intelligent and secure systems, empowering informed decision-making, and fortifying security by mitigating vulnerabilities and safeguarding data integrity.

Venkatesan, K et. al. [14] introduces hybrid consensus algorithms enhanced by machine learning (ML) approaches to manage the limitations and vulnerabilities of blockchain networks. While traditional consensus protocols often struggle with assuring compliance and are prone to cyber-attacks, this research proposes novel approaches like Delegated Proof of Stake Work (DPoS). By integrating ML for anomaly detection, cyber-attack prediction, and feature extraction, the proposed framework enhances the adaptability and energy efficiency of blockchain systems. However, challenges such as scalability, latency, resource demands, and adversarial threats remain key hurdles for real-world implementation.

Claudia Antal et. al. examines how blockchain technology can enhance the vaccination process. It proposes a system that ensures data integrity and prevents identity theft through secure beneficiary registration. Smart contracts are used to monitor vaccine distribution in accordance with producers' safe handling guidelines, keeping all network participants informed. A prototype was developed on the Ethereum test network, Ropsten, with results available for verification on Etherscan.

Ahsan Nazir et. al. [21] introduces a new method to improve IoT security by combining coordinated threat intelligence with blockchain technology and machine learning (ML) models. An iOS application serves as a central hub for reporting and sharing detected threats, with data securely stored on a blockchain network. The study employs Random Forest, Decision Tree, Ensemble, LSTM, and CNN models on the IoT23 dataset within Mutual Threat Intelligence architecture.

Li Li et. al. introduces a secure traceability framework integrating blockchain technology, a centralized database, and RFID tags. By leveraging blockchain's immutability for summary data and optimizing the SM3 algorithm, the system achieves a 30% improvement in efficiency, reducing execution time for 192-byte messages to 210 μ s. Traceability data is securely time-stamped and linked, with detailed information retained in the centralized database while unalterable summaries are recorded on the blockchain.

3. BACKGROUND

Warehouse management system as a part of warehouse is becoming complex task because of its operations and volume of data it handle. The purpose of this research is to demonstrate the employ blockchain technology for secure transactions and machine learning as predictive data analytics tool. The goal is to improve the efficiency of operations of warehouse and optimize the performance parameters. The transaction level information can be stored in the blockchain and smart contracts can be used to carry out the transactions processing. This

confirms the transparency between the parties involved in the business. Smart contracts play a role of online agreements based on meeting certain conditions.

The major issue in the warehouse is unpredictability of the operations required to fulfill the order and item request.[16] Product handling processes in the warehouse generates the large amount of data. This data needs to be recorded, stored and analyzed for predictive analysis. The data generated will be stored in the blocks of the blockchain server. Hence the physical space data is converted into the digital space for predictive data analysis through machine learning. Barcode system can be incorporated for digital tagging of the warehouse items and processes.[17-18]

Figure 1 illustrates the key components in designing a smart warehouse management system, highlighting the transformative roles of blockchain technology and machine learning. These cutting-edge technologies have applications across various fields, including supply chain management, healthcare, and manufacturing. In warehouse management systems (WMS), critical challenges such as space and route optimization, rapid item retrieval, demand forecasting, and transaction management are addressed. Smart contracts provide enhanced security, operational transparency, automated payments, and streamlined inventory management, while the machine learning module drives efficiency across the entire system.[19-20]



Figure 3.1: Aspects of Smart WMS

4. METHODOLOGY

4.1. Steps in consideration in WMS

In warehouse management system the process flow is as follows. Order Acceptance is a process of confirming and accepting an order received from a customer. Inventory Check is the procedure to verify the availability of items in stock before processing the order. Picking is the action of retrieving the items from the warehouse shelves as per the order requirements. Packing is the process of securely packing the picked items for shipment.

Documentation phase prepare and organize necessary paperwork and labels for the shipment. Carrier Coordination step arrange and schedule with the carrier service for order

pickup and delivery. Wait for Carrier is the time during which the packed orders are waiting for the carrier to arrive for pickup. Loading is the process of loading the packed orders onto the carrier's vehicle for transport.[21][22]

4.2. *Generation of Time Data*

We have used the Amazon sales report dataset for data analytics and model building. The contents of the data set are depicted in table 1.

Table 1. Amazon Sales Report

Name of the Data Set	Amazon Sale Report
No of records	128975
Item timing parameters generated	Wait for carrier
	Order acceptance adjusted
	Inventory check adjusted
	Picking adjusted
	Packing adjusted
	Documentation adjusted
	Carrier coordination adjusted
	Loading adjusted
	Total Time

Following functions are used to generate the synthetic time data.

- **Time Ranges Based on Buying Patterns:** The function defines four specific time ranges representing typical buying patterns throughout the day: morning peak (8 AM to 12 PM), afternoon peak (12 PM to 3 PM), evening peak (5 PM to 8 PM), and off-peak (8 PM to 12 AM).
- **Weighted Selection of Time Ranges:** Each time range is assigned a weight reflecting the likelihood of purchases occurring within that period. These weights simulate observed buying behavior: morning peak (30%), afternoon peak (40%), evening peak (25%), and off-peak (5%).

- **Random Selection within Time Ranges:** Using the weights, a time range is randomly selected to simulate the time of purchase. This selection process ensures that the synthetic time data aligns with typical buying patterns.
- **Random Time Generation within Selected Range:** After selecting a time range, the function generates a random time within this range by randomly selecting an hour, minute, and second. This approach produces a diverse set of times while adhering to the overall buying behavior trends.

Pseudo Code for generation of time data

Function generate_synthetic_time():

 Define time ranges:

```
morning_peak = (8, 12)    // 8 AM to 12 PM
afternoon_peak = (12, 15) // 12 PM to 3 PM
evening_peak = (17, 20)   // 5 PM to 8 PM
off_peak = (20, 24)       // 8 PM to 12 AM
```

 Define weights for each time range:

```
weights = [0.3, 0.4, 0.25, 0.05]
```

 Select a time range based on weights:

```
selected_range = random.choices(time_ranges, weights)
```

 Generate a random time within the selected range:

```
hour = random.randint(selected_range[0], selected_range[1] - 1)
minute = random.randint(0, 59)
second = random.randint(0, 59)
```

 Return time(hour, minute, second)

4.3. *Generation of Raw Elapse Time data for each step of WMS*

For each step in the WMS process (e.g., Order Acceptance, Inventory Check), a base time (in minutes) and an associated randomness (standard deviation) were defined. These values represent the average expected time and the variability for each step. To generate realistic time data that reflects the natural variability of each step while ensuring all values are positive and non-zero, a truncated normal distribution was used. The function uses PDF (Probability Density Function) and CDF (Cumulative Distribution Function). This

distribution is bounded to ensure times remain within a plausible range, avoiding negative or excessively high values. Following is the formula for truncated normal distribution.

$$f(x|\mu, \sigma, a, b) = \frac{\phi(\frac{x-\mu}{\sigma})}{\sigma(\Phi(\frac{b-\mu}{\sigma}) - \Phi(\frac{a-\mu}{\sigma}))} \quad (4.3.1)$$

$\phi(\frac{x-\mu}{\sigma})$ is the PDF of standard normal distribution

$\Phi(\frac{a-\mu}{\sigma})$ is the CDF of standard normal distribution

For each step, the mean and standard deviation were set to the base time and randomness, respectively. The bounds were determined to be slightly above zero (0.01) and up to three times the base time, ensuring realistic yet varied durations. For each step, the truncated normal distribution function was applied to generate a column of times. This function ensured that the generated times varied around the base time according to the defined randomness, producing realistic and variable step durations for each entry in the dataset.

4.4. Adjustment for load in elapsed time of WMS steps

The function for a load calculation calculates the current load by counting the number of records in the dataset that have the same hour as the current row's timestamp. This load represents the number of tasks or processes occurring within that specific hour. The raw elapsed time for a given step is adjusted using a load factor, which scales the time based on the calculated load. The formula used is

adjusted time = raw time x (1 + load factor x load)

This adjustment increases the elapsed time proportionally to the load, simulating delays or extended processing times due to higher load. A lambda function is used to calculate and apply adjustment to time data of each step of WMS. This lambda function is passed into df.apply function of dataframe which applies the adjustment to each step according to calculated load. A simple arithmetic sum is taken for all the adjusted times of WMS steps to calculate total time taken for all steps to complete within the WMS. This field is added to the dataframe for further usage. The table 2 below shows the statistics of the elapsed time for given dataset.

Table 2. Statistics of Adjusted Times

Name	Min (min.)	Max (min.)	Mean (min.)	Mean (hr.)	Mean (days)
Order Acceptance	0.14	1574.17	417.47	6.96	0.29
Inventory Check	0.15	6531.87	1670.18	27.84	1.16
Picking	0.22	1294.98	406.87	6.78	0.28
Packing	0.72	310.22	108.42	1.81	0.08

Documentation	0.08	528.57	139.03	2.32	0.10
Carrier Coordination	0.20	267.75	94.83	1.58	0.07
Loading	0.45	398.50	135.42	2.26	0.09
Wait for Carrier	0.47	8619.00	2960.71	49.35	2.06
Total Time	137.32	9084.79	2972.23	49.54	2.06

4.5. Demand Prediction

In data preprocessing phase the dataset is read and preprocessed by converting datetime columns, handling missing values, and encoding categorical variables. Numerical features are scaled using StandardScaler to ensure the data is centered around zero with a unit standard deviation, thereby enhancing the effectiveness of the machine learning model. The time series data is prepared using TimeseriesGenerator, which creates sequences of a specified length (sequence_length) from the scaled features to be used as input for the LSTM model. This generator pairs the input sequences with the corresponding target values (quantities). An LSTM model is built using Keras, consisting of an LSTM layer with 50 units and a Dropout layer to prevent overfitting. The model is trained on the generated sequences to predict the quantity (Qty) of orders. The training is conducted for a predefined epochs, during which the model learns to capture the temporal dependencies in the data.

After training, the model's predictions are evaluated against the actual values using metrics. The model showed Pearson correlation coefficient of 0.9908 showing very accurate demand prediction. The model achieved a very low MSE loss of 0.0165 and RMSE of 0.0200. The actual and predicted quantities are plotted over different time intervals (daily, hourly, weekly) to visualize the model's effectiveness and the reliability of demand predictions. The following figure 2 shows the graph of actual versus predicted daily quantity over time.



Figure 4.5.1. Plot of Actual vs Daily Quantity over Time

5. CONCLUSION

In this research, we analyzed the integration of Blockchain technology and machine learning to develop a smart Warehouse Management System (WMS). By combining these two transformative technologies, we aimed to improve the performance of traditional WMS. Using an Amazon sales report as the dataset, we generated synthetic timestamps to simulate real-time conditions and analyzed each WMS material handling step accordingly. An LSTM model was constructed to evaluate the data, incorporating a demand prediction module to track actual versus forecasted daily quantities over time, alongside a total turnaround time prediction. Our results demonstrate improved accuracy in demand forecasting and reduced turnaround times within the experimental data model, underscoring the potential of our approach to optimize WMS performance.

6. REFERENCES

- [1] Kayikci, S., Khoshgoftaar, T.M., ‘Blockchain meets machine learning: a survey’, *Journal of Big Data*, vol. 11, no. 9, 2024. doi: 10.1186/s40537-023-00852-y.
- [2] El Hathat, Z., Venkatesh, V.G., Sreedharan, V.R., *et al.*, ‘Leveraging greenhouse gas emissions traceability in the groundnut supply chain: Blockchain-enabled off-chain machine learning as a driver of sustainability’, *Information Systems Frontiers*, 2024. doi: 10.1007/s10796-024-10514-w.
- [3] Khan, S., Haleem, A., Husain, Z., *et al.*, ‘Barriers to blockchain technology adoption in supply chains: The case of India’, *Operations Management Research*, vol. 16, pp. 668–683, 2023. doi: 10.1007/s12063-023-00358-z.
- [4] Hirata, E., Lambrou, M., Watanabe, D., ‘Blockchain technology in supply chain management: Insights from machine learning algorithms’, *Maritime Business Review*, vol. 6, no. 2, pp. 114–128, 2021. doi: 10.1108/MABR-07-2020-0043.
- [5] Wisetsri, W., Syam, E., Alanya-Beltran, J., Kulkarni, G. R., Vardhan Reddy, R. K., Alam Sheikh, M. F., ‘Assessing and comparing the role of machine learning (ML) and supply chain management (SCM) towards enhancing e-commerce’, *Proc. 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE)*, Greater Noida, India, pp. 2574–2577, 2022. doi: 10.1109/ICACITE53722.2022.9823586.
- [6] Ni, L., Irannezhad, E., ‘Performance analysis of LogisticChain: A blockchain platform for maritime logistics’, *Computers in Industry*, vol. 154, 104038, 2024. doi: 10.1016/j.compind.2023.104038.
- [7] Duan, K., Pang, G., Lin, Y., ‘Exploring the current status and future opportunities of blockchain technology adoption and application in supply chain management’, *Journal of Digital Economy*, 2024. doi: 10.1016/j.jdec.2024.01.005.
- [8] Stopfer, L., Kaulen, A., Purfürst, T., ‘Potential of blockchain technology in wood supply chains’, *Computers and Electronics in Agriculture*, vol. 216, 108496, 2024. doi: 10.1016/j.compag.2023.108496.
- [9] Sunmola, F., Burgess, P., ‘Transparency by design for blockchain-based supply chains’, *Procedia Computer Science*, vol. 217, pp. 1256–1265, 2023. doi: 10.1016/j.procs.2022.12.324.
- [10] Wannenwetsch, K., Ostermann, I., Priel, R., Gerschner, F., Theissler, A., ‘Blockchain for supply chain management: A literature review and open challenges’, *Procedia Computer Science*, vol. 225, pp. 1312–1321, 2023. doi: 10.1016/j.procs.2023.10.119.

- [11] Dong, Z., Liang, W., Liang, Y., *et al.*, ‘Blockchained supply chain management based on IoT tracking and machine learning’, *Journal of Wireless Communications and Networking*, 2022, 127, 2022. doi: 10.1186/s13638-022-02209-0.
- [12] Peng, X., Zhang, X., Wang, X., *et al.*, ‘Construction of rice supply chain supervision model driven by blockchain smart contract’, *Scientific Reports*, vol. 12, 20984, 2022. doi: 10.1038/s41598-022-25559-7.
- [13] Biswas, K., Muthukkumarasamy, V., Bai, G., *et al.*, ‘A reliable vaccine tracking and monitoring system for health clinics using blockchain’, *Scientific Reports*, vol. 13, 570, 2023. doi: 10.1038/s41598-022-26029-w.
- [14] Venkatesan, K., Rahayu, S. B., ‘Blockchain security enhancement: An approach towards hybrid consensus algorithms and machine learning techniques’, *Scientific Reports*, vol. 14, 1149, 2024. doi: 10.1038/s41598-024-51578-7.
- [15] Hande, K., Chandak, M. B., ‘Role of blockchain technology and machine learning in design of smart and secure warehouse management system: A survey’, *International Journal of Next-Generation Computing*, vol. 13, no. 5, pp. 1274–1279, Nov. 2022. doi: 10.47164/ijngc.v13i5.920.
- [16] Suhail, S., Hussain, R., Jurdak, R., Oracevic, A., Salah, K., Hong, C. S., Matulevičius, R., ‘Blockchain-based digital twins: Research trends, issues, and future challenges’, *ACM Computing Surveys*, vol. 54, no. 11s, Article 240, Jan. 2022. doi: 10.1145/3517189.
- [17] Ren, Z., Wan, J., Deng, P., ‘Machine-learning-driven digital twin for lifecycle management of complex equipment’, *IEEE Transactions on Emerging Topics in Computing*, vol. 10, no. 1, pp. 9–22, Jan.–Mar. 2022. doi: 10.1109/TETC.2022.3143346.
- [18] Ma, X., Du, W., Li, L., *et al.*, ‘Examining the nexus of blockchain technology and digital twins: Bibliometric evidence and research trends’, *Frontiers of Engineering Management*, vol. 11, pp. 481–500, 2024. doi: 10.1007/s42524-024-0306-4.
- [19] Abrar, I., Sheikh, J. A., ‘Current trends of blockchain technology: Architecture, applications, challenges, and opportunities’, *Discover Internet of Things*, vol. 4, no. 7, 2024. doi: 10.1007/s43926-024-00058-5.
- [20] Unhelkar, B., Joshi, S., Sharma, M., Prakash, S., Mani, A. K., Prasad, M., ‘Enhancing supply chain performance using RFID technology and decision support systems in the Industry 4.0—A systematic literature review’, *International Journal of Information Management Data Insights*, vol. 2, no. 2, 100084, 2022. doi: 10.1016/j.jjime.2022.100084.
- [21] Nazir, A., He, J., Zhu, N., Wajahat, A., Ullah, F., Qureshi, S., Ma, X., Pathan, M. S., ‘Collaborative threat intelligence: Enhancing IoT security through blockchain and machine learning integration’, *Journal of King Saud University – Computer and Information Sciences*, vol. 36, no. 2, 101939, 2024. doi: 10.1016/j.jksuci.2024.101939.
- [22] Tufano, A., Accorsi, R., Manzini, R., ‘A machine learning approach for predictive warehouse design’, *The International Journal of Advanced Manufacturing Technology*, vol. 119, no. 3–4, pp. 2369–2392, 2022. doi: 10.1007/s00170-021-08035-w.

Biographies



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