Wireless Personal Communications
https://doi.org/10.1007/s11277-024-11017-2

RESEARCH

6G-Driven Cyber Physical Supply Chain Model for Supporting E-Commerce Industries

Xianyu Fu[1]

Accepted: 30 March 2024

Abstract

The evolution of e-commerce trade becomes more important also the integration of 6G generation into cyber-physical systems presents the transformative ability to supply chain control. This paper proposes a novel 6G-driven cyber-physical supply chain version designed for e-commerce industries, aiming to address the growing demands for performance, reliability, and actual-time monitoring in logistics operations. By connecting the abilities of 6G, including Ultra-Reliable Low Latency Communications, massive Machine Type Communication, and Enhanced Mobile Broadband, these version gives a complete approach to enhance the supply chain's performance from manufacturing to delivery. In the existing methods, the e-commerce sequential processing is not addressed. In the proposed work, the sequential data is processed, and the tracking is efficiently predicted, which makes e-commerce management. The proposed research used RNN-LSTM method for supporting E-Commerce industries based on 6G-driven cyber physical system model. A key innovation of the proposed model is its adaptive, self-optimizing, which dynamically adjusts to changes in call for, deliver situations and network status. This flexibility ensures that e-trade agencies can maintain the most efficient stock stages, reduce lead instances, and enhance purchaser preference through timely and correct deliveries. Implementing this 6G-driven cyber-physical supply chain version guarantees vast operational performance, sustainability, and client experience improvements. The proposed method is compared with existing methods such as CNN-LSTM, CapsNet and CNN-BiLSTM. The proposed method enhances the data transmission, improves the e-commerce management for taking better decisions.

Keywords 6G-driven · Cyber-physical · Supply chain model · E-commerce · Industries · Machine learning

✉ Xianyu Fu
m13408061350@163.com

[1] Sichuan Changjiang Vocational College, Chengdu 610000, China

1 Introduction

The advent of the 6G generation heralds a transformative generation for the digital financial system inside the e-commerce zone, wherein the mixing of cyber-physical systems (CPS) is essential for reinforcing operational performance, sustainability, and client pleasure. This paper introduces the establishment of a 6G-driven cyber-physical supply chain version designed to guide and revolutionise the e-commerce industry [1]. By leveraging the extraordinary abilities of 6G, including its excessive data transmission, low latency, and advanced connectivity features, this model aims to seamlessly combine digital and physical elements of the supply chain, enabling real-time tracking, predictive analytics, and self-sufficient operations [2].

The proposed version addresses the growing complexity and dynamic demands of modern-day e-trade markets, supplying a scalable and flexible framework that can adapt to the evolving desires of groups and consumers [3]. It exploits the energy of superior technologies such as the Internet of Things (IoT), Artificial intelligence (AI), Machine Learning (ML), and blockchain, all of which can be amplified via the robustness and speed of 6G networks. This integration facilitates a more responsive, transparent supply chain that is able to predict demand control, more advantageous stock optimisation, and dynamic logistics-making plans [4].

Competition brings many challenges for organisations operating in the marketplace. Today's organisations must re-engineer their commercial enterprise patterns to simultaneously deliver something innovative and superficial to the market [5]. These characteristics are regular for Industry 4. 0, followed by increasing corporations. The Enterprise 4.0 Idea responds to the demanding situations introduced with cutting-edge methods. Based on this, exchanging commercial enterprise models and supply chains in groups is necessary to integrate technological improvements, helping create values primarily based on facts [6]. The version should be based on an underlying process that creates a cost for the client. Digitalisation influences all industries, which increases performance.

Blockchain can be carried out in any transaction to store and verify the product's existence cycle. Economic ledgers are the most used instances for blockchain. Blockchain generation isn't always restrained to the supply chain and its various programs, such as surveying, possession control, power delivery, protecting essential civil infrastructure, digital fitness information, etc. In [7, 8], the authors proposed a supply chain to rearrange the cutting-edge necessary database systems with blockchain to provide transparent information. Authentication and tracking of the supply chain have become urgent issues for the industry and its stakeholders. The authors have highlighted that blockchain in a food supply chain may be carried out at numerous stages: production, processing, storage, distribution, retail, and administration levels. In addition, the authors [9, 10] have reviewed the usage and improvement of Radio Frequency Identification (RFID) inside blockchain surroundings and have identified the pros and cons of the use of RFID and blockchain generation for agriculture and the food delivery chain [11]. The authors have proposed a conceptual design for building an Agri-meals deliver-chain traceability device.

The RNN-LSTM networks are particularly suited for analysing time-series data, a common characteristic in supply chain logistics, such as demand forecasting, inventory levels, and shipment tracking. Unlike traditional models, RNN-LSTMs can process data sequences, learning and remembering the context from previous inputs to make more accurate predictions about future supply chain needs. This capability is crucial for e-commerce industries with dynamic market demands and complex logistic operations. Integrating RNN-LSTM models in 6G environments enhances supply chain visibility and monitoring by efficiently processing real-time data from sensors and IoT devices. This real-time processing ability ensures that e-commerce businesses can track the status of goods throughout the supply chain, from manufacturing to delivery to the end customer, enabling proactive management of potential disruptions.

The main contribution of the suggested work is given below:

- This work uses the RNN-LSTM method to support E-commerce industries based on 6G- cyber-physical system (CPS). It efficiently tracks the products and resources through the supply chain.
- Initially, the data is collected, then flows into CPS, and then the RNN-LSTM method is used for making decisions.
- This model aims to integrate the high-speed, low-latency capabilities of 6G networks with the predictive analytics and sequence modelling strengths of RNN-LSTM architectures to improve supply chain operations.
- Finally, the proposed method enhances the performance of e-commerce industries, and by integrating the 6G network, it provides speed data transfers and efficient predictive analysis.

The remainder of our research paper is as follows: The related research on deep learning, 6G-driven, cyber-physical supply chain and E-commerce industries is covered in Sect. 2. The suggested work's general working technique and algorithmic procedure are illustrated in Sect. 3. The outcomes and application of the suggested approach are assessed in Sect. 4. The job is concluded, and the outcome evaluation is covered in Sect. 5.

2 Related Works

Nowadays, a tremendous procedure of technical methods has been applied to enhance the exceptionality of logistics carriers promoted by using the pattern of industry 4. 0. In specific, the superior sensing and computing technologies inclusive of internet-of-things (IoT), cloud computing and edge computing are broadly deployed to collect cyber-physical system (CPS) infrastructures, thereby helping the efficient collection, transmission, processing, and evaluation of information [12]. Within the logistics CPS, the information acquisition and transmission additives act because the cyber additives and the entities are controlled and act as physical components. For example, the stock control device works in a CPS style such that it achieves the marketplace facts through the statistics system and makes decisions on replenishment to maintain an inexpensive inventory degree [13]. Based on this infrastructure, the enormous deployment of Artificial intelligence (AI) is enabled to facilitate the tracking, operation and decision-making inside the logistics subject, thereby improving the performance and reliability of logistics in place of the conventional tactics [14].

Based on the findings, we will declare that in the digitalisation surroundings, there may be a need to trade the price chain inside the region of research and improvement, manufacturing, and income in a simple way that adapts to the dynamic market [15, 16]. The impact of digital Transformation on the price chain is no longer the most compelling subject to the precise fee chain; however, it additionally emphasises the position of records inside the digital value chain, which emerges as a new element in it [17]. The basis of a virtual value chain is the information era. As a part of the virtual transformation, statistics permeate all primary and secondary sports of the cost, affecting every supply chain link of cost creation. Consequently, the virtual price chain originates within the physical value chain and is a part of it [18, 19]. Therefore, it's miles essential for organisations to analyse the effect of digital transformation at the cost chain from a records existence cycle angle.

Cyber-physical manufacturing systems are self-governing, capable of making choices based on real-time statistics and digital simulation algorithms, inspection of previous movements' results, and studying by-products [20, 21]. Enterprise resource planning methods, cyber-physical manufacturers, artificial intelligence-based algorithms, and manufacturing systems are software programs that manipulate providers in decentralised smart factories [22]. Wireless fixed sensors are essential for sending information to the supply chain and interacting with the industrial environment. The industrial Internet of Things allows sensor interaction and non-stop connection through digital simulation algorithms [23], evolved on cyber-physical device-based actual-time tracking, big data-driven selection-making strategies, and wireless sensor networks [24]. Human-system interaction is important in intelligent production, considering certain tasks cannot be computerised [25]. Good factories can produce intelligent objects with sensors that are a resource in localisation and life cycle monitoring in addition to manual production, appreciably simplifying preservation [26].

Within the present-day logistics in CPS, data collection is enabled by using wide networking technologies, which bureaucracy an IoT architecture. The IoT architecture in logistics structures can typically be divided into four layers: Sensing, network, processing, and alertness [27, 28]. Taking advantage of this structure, the sensing layer accumulates the statistics of physical entities using sensing techniques, video digicam, and LiDAR. In the end, the collective information is forwarded to the processing layer for the service department and computing through the network layer, in which the communications techniques like wireless sensor network (WSN), wireless Local Area Networks (WLAN), wi-fi and 5G Communications can be followed entirely based on the requirements of the application situations [29, 30].

Heterogeneity implies that the agents in the system have different capabilities, models, or functions[32]. Integrating DBNs with IoT-based agricultural systems involves processing and analysing the data collected from various IoT devices scattered across the farm[33]. AI systems can continuously update forecasts based on the latest data, allowing companies to adapt quickly to market changes[34, 35]. These relay nodes are powered wirelessly, often through technologies like RF (radio frequency) energy harvesting, which allows them to operate without wired power sources[36].

The various literature works are discussed above. The e-commerce, manufacturing, logistics, and supply chains are interconnected to send the products to the market with quality and security. The wireless network helps track supply chain data and updates the situation. However, security of data is highly concerning over communication network. The main requirement of a business enterprise is fast and secure communication to protect the business details. This research proposed 6G-cyber physical model for e-commerce supply chain to improve the data communication performance.

3 Proposed Methodology

The proposed methodology for supporting E-commerce industries uses RNN-LSTM based on 6G-driven Cyber Physical system (CPS). Initially, the data is collected by IoT sensors from E-commerce industries. Next, the data is pre-processed, then the pre-processed data is fed into CPS model. The Cyber Physical system's fast and secure data transmission enhances predictive analysis and decision making. Finally, the RNN-LSTM method is used for training and testing the datasets. In Fig. 1 shows the architecture of proposed work.

RNNs are specially designed to process sequential data, making them appropriate for initial layers where raw sequential inputs from E-commerce (like text, time series data) are directly fed as input. They can successfully capture the temporal dependencies in the input sequence. Placing RNN layers before LSTM layers can act as a feature extraction mechanism in this research work. The RNN can learn to recognize preliminary patterns or features in input data, which are then further processed and refined by the LSTM layers. Starting with RNN layers for feature extraction helps in terms of computational efficiency and learning rate od data. Basic data patterns are analysed by RNN and further LSTM builds to understand more complex sequences very efficiently. By using RNN layers before LSTM helps in creating smoother gradients flow for sequences and ensures LSTM receives more refine input for the process. It reduces LSTM burden on dealing with raw sequential data.

4 Data Collection

Data collection for a 6G-driven cyber-physical supply chain model that supports e-commerce industries using RNN-LSTM (Recurrent Neural Networks—Long Short-Term Memory) involves a sophisticated approach to gather, process, and analyse data to forecast

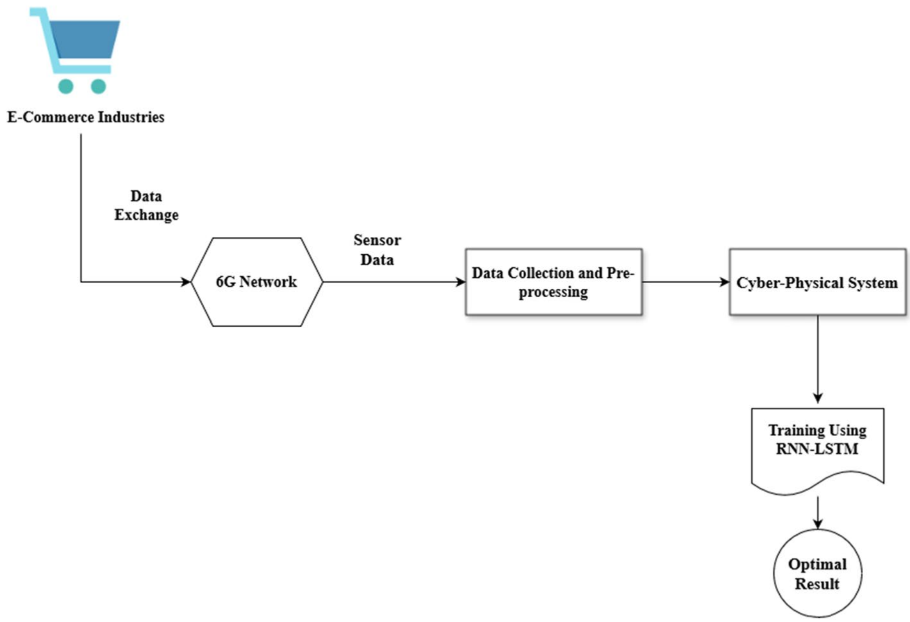

Fig. 1 Architecture of proposed work

demand, optimise inventory, and enhance supply chain operations. This involves multiple steps tailored to leverage the speed, reliability, and low latency of 6G technology, coupled with the predictive power of RNN-LSTM models.

4.1 Dataset Description

Eurostat database [31] is used in this work. E-commerce data from Eurostat can offer insights into online sales trends, the penetration of e-commerce among businesses, the proportion of individuals making online purchases, and cross-border e-commerce activities within the European Union (EU) and beyond. This category includes data on the proportion of businesses that make electronic sales (e-sales), e-commerce sales as a percentage of total sales, and breakdowns by sector, size class, and country. The data can be downloaded in various formats, including Excel, CSV, and TSV, facilitating easy integration with analytical tools. For real-time tracking of inventory and shipments. 6G technology enhances the capability to process data from IoT devices due to its high bandwidth and low latency.

4.2 Designing Cyber-Physical System Architecture for E-Commerce Industries

The Cyber-Physical system (CPS) structure is designed for e-commerce industries and includes growing a framework that integrates the physical components of the supply chain with the cyber elements of data processing, analysis, and choice-making, facilitated by advanced technologies like IoT, AI, and probably 6G connectivity. This structure objectives to beautify performance, improve reliability, and enable actual-time responsiveness across the e-trade supply chain. In this work two types of layer is used.

4.3 Physical Layer

- *Warehouses and achievement center* It prepared with automatic systems for stock control, robotics for choosing and packing, and sensors for tracking inventory levels.
- *Transportation and logistics* Motors geared up with GPS and sensors to screen conditions and signal the movement of products in real time. This includes vast distance transport drones or independent motors where viable.
- *Retail factors and cease users* Integration of patron-going through systems, like mobile apps or websites, with the physical delivery of products.

4.4 4.4 Cyber Layer

- *Information infrastructure* A large amount of e-commerce information is stored in cloud computing infrastructure, which helps the supply chain access the information.
- *Analytics and decision structures* AI and device mastering models for predictive analytics, demand forecasting, course optimisation, and stock management.
- *Manage systems* software program structures that provide real-time tracking and management over physical structures, facilitating automated choice-making primarily based on facts analytics.

6G for its low latency, excessive reliability, and high bandwidth abilities ensures continuous communication among physical and cyber systems. A network of sensors and actuators embedded throughout the supply chain provides real-time records on inventory, environmental situations, and machine performance. For more complex processing and lengthy-term records garage, helping advanced analytics, device gaining knowledge of, and global supply chain optimisation. Adopting industry-preferred data codecs and verbal exchange protocols to ensure interoperability among one-of-a-kind structures and components within the CPS. Offering APIs to integrate with offerings, such as price processors, e-commerce structures, and logistics services, improving the environment's flexibility and capability. It allows delivery chain managers to visualise statistics, receive signals, and control operations in actual time for operational monitoring and control.

4.5 Data Management for E-Commerce Industries Based on 6G Network

The advent of 6G networks promises transformative changes in data management and analytics for e-commerce industries, building on the capabilities introduced by 5G. 6G is anticipated to provide even faster data speeds, lower latency, higher reliability, and greater device connectivity density. These improvements will enable e-commerce businesses to harness real-time data analytics, enhance customer experiences, and streamline operations more efficiently. In e-commerce, this means deploying edge computing nodes near users, warehouses, and distribution centres. Edge computing enables faster response times, reduces network congestion, and enhances data privacy and security.

With 6G-enabled data analytics, e-commerce platforms can deliver highly personalised shopping experiences tailored to individual preferences and behaviour. By analysing user data in real time, including browsing history, purchase patterns, and demographic information, platforms can offer personalised product recommendations, customised promotions, and interactive shopping experiences, increasing customer engagement and loyalty. Data analytics powered by 6G networks can optimise various aspects of the supply chain, including inventory management, logistics, and order fulfilment. By analysing supply chain data in real-time, e-commerce companies can identify inefficiencies, streamline operations, and reduce costs. Predictive analytics can also help anticipate supply chain disruptions and proactively mitigate risks, ensuring continuity of operations. E-commerce platforms can leverage data analytics to detect and prevent fraudulent activities like payment fraud, identity theft, and account takeovers. By analysing transaction data, user behaviour patterns, and device fingerprints, machine learning algorithms can identify suspicious activities in real time and trigger automated fraud prevention measures, such as transaction verification and user authentication.

4.6 RNN-LSTM Method for Training Data

After the data preparation, the dataset is transformed into sequences that the LSTM model can process. Each input sequence is a set of consecutive data points from the time series, and the output is the value you want to predict (e.g., next month's sales).

4.7 Recurrent Neural Network (RNN)

Recurrent Neural Networks (RNN) and their superior variation, long brief-term memory (LSTM) networks, offer tremendous blessings for e-trade industries by leveraging sequential data for prediction and analysis. Those deep mastering models are uniquely appropriate for responsibilities concerning time-collection facts or any facts wherein the series and context are remembered. RNN-LSTM fashions can examine historical income records, considering developments, seasonal patterns, and product lifecycles to forecast future demand for products appropriately. This aids in stock control, assisting corporations in holding top-quality stock tiers to fulfil consumer demand without overstocking or stockouts. By studying customers' browsing and purchase histories, RNN-LSTM models can expect destiny buying behaviours, consisting of potential purchases, probable product hobbies, or even the chance of a customer returning.

An RNN can be described with the following equations, which detail how it updates its hidden state H_t and produces an output Y_t at each time step t:

Hidden state update

$$H_t = f(UX_t + WH_{t-1} + b_h) \tag{1}$$

Output

$$Y_t = g(VH_t + b_y) \tag{2}$$

where:

H_t is the hidden state at time t, containing information learned from time steps 1 to t. X_t is the input at time step t. Y_t is the output at time step t. U, W, and V are the weight matrices for input-to-hidden, hidden-to-hidden, and hidden-to-output layers respectively. b_h and b_y are bias terms for the hidden and output layers respectively. $f(\cdot)$ and $g(\cdot)$ are activation functions. Common choices for $f(\cdot)$ include the tanh or ReLU function, and for $g(\cdot)$ the softmax function (for classification tasks) or linear activation (for regression tasks).

The hidden state update equation combines the current input X_t with the previous hidden state H_{t-1} to generate the current hidden state H_t. This is where the RNN has its memory. The function f is typically a non-linear activation function like tanh or ReLU, which helps to capture complex patterns and relationships in the data. The output equation calculates the output Y_t based on the current hidden state H_t. The choice of the function gg depends on the specific task (e.g., softmax for classification).

4.8 LSTM

LSTMs improve upon RNNs by addressing the vanishing gradient problem, allowing the model to retain information over longer sequences. An LSTM unit comprises three gates (forget gate, input gate, and output gate) and a cell state, which helps it to remember or forget information. The equations for an LSTM cell are:

Forget gate

$$f_t = \sigma(W_f \cdot [h_t - 1, x_t] + b_f) \tag{3}$$

Input gate

$$i_t = \sigma(W_i \cdot [h_t - 1, x_t] + b_i) \tag{4}$$

$$\widetilde{C}_t = tanh(W_C \cdot [h_t - 1, x_t] + b_c) \tag{5}$$

Cell state update

$$C_t = f_t * C_{t-1} + i_t * \widetilde{C}_t \tag{6}$$

Output gate

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{7}$$

$$h_t = o_t * tanh(C_t) \tag{8}$$

where:

f_t, i_t, o_t are they forget gate, input gate, and output gate vectors, respectively, $\widetilde{C}_t$ is the candidate vector for addition to the cell state, C_t is the cell state vector, h_t is the hidden state vector, W and b terms represent the weights and biases for different parts of the network, x_t is the input vector at time step t, $h_t - 1$ is the hidden state from the previous time step, C_{t-1} is the cell state from the previous time step, σ denotes the sigmoid activation function, *tanh* represents the hyperbolic tangent activation function. In Fig. 2 structure of RNN-LSTM.

5 Result Analysis

The proposed methodology for supporting e-commerce using RNN-LSTM based on 6G-based Cyber Physical System. To simulate an RNN-LSTM model, especially for applications in e-commerce data analysis such as demand forecasting or customer behavior analysis, several key parameters need to be configured. In this work, Eurostat dataset is used for evaluation. In this Eurostat dataset, Di dataset is used in this work. The Di dataset

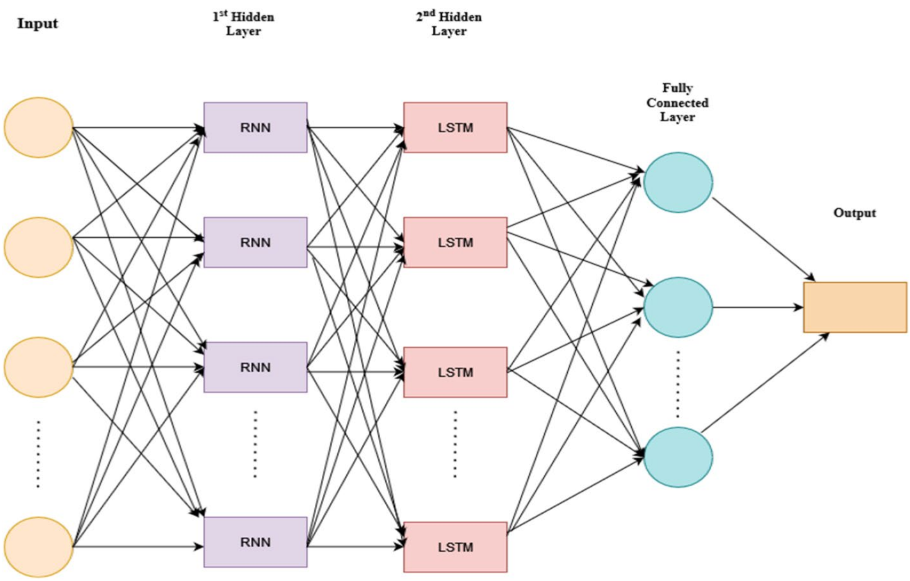

Fig. 2 Structure of RNN-LSTM

is enterprises with a digital intensity index is used. In Table 1 shows the simulation parameters of RNN-LSTM.

The Result analysis for e-commerce industries with 6G network uses Recurrent Neural Networks (RNN) with long short-time period memory (LSTM) models involves comparing the performance of these models in numerous programs with demand forecasting, consumer conduct evaluation, and stock control. The Di dataset is evaluated by using accuracy, precision, recall, and f1-score.

The simulation's accuracy, expressed in Eq. (9), indicates how effectively the model works across classes.

$$Accuracy = \frac{Total\ number\ of\ truly\ classified\ samples}{Total\ Samples} \tag{9}$$

The precision of the simulations is an assessment of their capacity to detect true positives, and it is computed using Eq. (10).

$$Precision = \frac{TP}{TP + FP} \tag{10}$$

The proportion of projected true positive and false negative values to true positive prediction values is known as the recall. Equation (11) represents the calculation.

$$Recall = \frac{TP}{TP + FP} \tag{11}$$

The model's total accuracy, or F1 score, strikes a positive class balance between recall and precision. Equation (12), which represents the calculation, is used.

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{12}$$

The accuracy, precision, recall, and F1 scores are displayed in Table 2. Compared to current methods, these are some of the most widely used performance measures and are practical.

The accuracy of Recurrent Neural Networks (RNN) and Long-Short term memory (LSTM) fashions in e-trade packages can vary broadly depending on several factors, such as the complexity of the project, the high quality and quantity of the training data and the way properly the model is tuned and optimised. RNNs and LSTMs are particularly ideal for responsibilities involving sequential records or time series analysis, making them ideal

Table 1 Simulation parameter

Parameters	Values
Number of layers	1–3
Units per layer	50–500
Batch size	32,64,128
Epochs	100
Learning rate	0.001,0.01
Optimizer	Adam
Activation Function	tanh, RELU
Dropout Rate	0.5
Input size	Word vector

Table 2 Experimental results of the dataset Di

Methods used	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
CNN-LSTM	90	83	85	79
CapsNet	76	79	81	87
CNN-BiLSTM	83	87	90	84
Proposed	96	97	96	95-

for numerous e-commerce packages along with a call for forecasting, consumer behaviour prediction, and customised advice structures. In e-commerce, accurate demand forecasting, customer behaviour analysis, or recommendation structures can beautify operational performance and patron pleasure. Even as it is tough to pinpoint a selected accuracy variety without context, RNN-LSTM fashions in well-configured situations have been recognised to attain high accuracy levels. Figure 3 shows the evaluation of Accuracy.

The use of Recurrent Neural Networks (RNN) and long-short term memory (LSTM) networks to achieve precision in e-commerce industries entails leveraging those deep mastering fashions to research and are expecting sequential facts correctly. These patterns are specially nicely desirable for duties that require knowledge time-series records or sequences, consisting of consumer behaviour over time, income trends, and stock tiers. Predicting future product demand based totally on ancient sales statistics, seasonal trends, and promotional sports. RNN-LSTM fashions can capture temporal dependencies and patterns in sales data, enabling extra accurate inventory degree changes and reducing both overstock and stockouts. Studying sequences of client movements (e.g., clicks, purchases, searches) to expect destiny conduct, consisting of the probability of

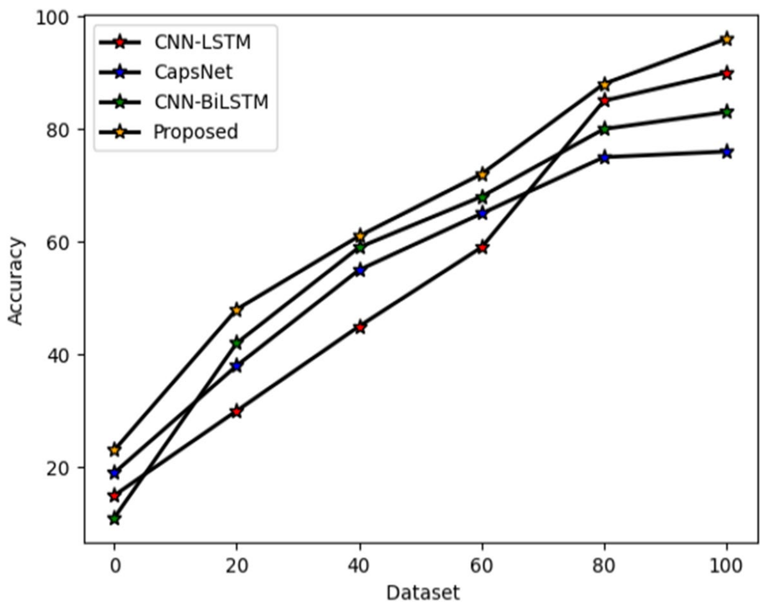

Fig. 3 Evaluation of accuracy

a purchase or the potential hobby in unique product categories. This allows for personalised advertising and marketing and focused product guidelines. Dynamically adjusting costs primarily based on traits in call for and supply, competitor pricing, and marketplace situations. RNN-LSTM fashions can manner historic pricing records and sales overall performance to perceive the most fulfilling pricing strategy that maximizes earnings at the same time as retaining competitiveness. In Fig. 4 shows the evaluation of precision. Comparing with all the other existing methods, the proposed method achieves higher precision.

The Recurrent Neural Networks (RNN) and long short-term memory (LSTM) fashions, normally refers to the version's potential to properly become aware of all relevant instances from the dataset. For e-commerce, those instances will be anything from product guidelines and purchaser churn predictions to fraud detection. Recall is vital in eventualities wherein lacking an advantageous instance (e.g., failing to recommend a product a person would love, not figuring out a user level to churn, or lacking a fraudulent transaction) ought to have big implications. In the context of RNN-LSTM models for e-trade, enhancing, don't forget the way, making sure that the version misses as few relevant instances as possible. For example, in a product recommendation gadget, an excessive price shows that the device is a hit in identifying most of the goods a consumer is likely to be interested in. Further, for fraud detection, excessive bear-in-mind approaches to the system are powerful in figuring out most fraudulent transactions. Figure 5 shows the evaluation of Recall. The proposed method achieves the highest recall compared with existing methods.

To compute the F1-score for e-trade industries the use of an RNN-LSTM model, you would commonly be concerned in a class task, together with client churn prediction, product recommendation, or sentiment analysis from customer evaluations. The F1-score measures a test's accuracy and considers both the precision and the don't forget of the test to compute the score. It's particularly beneficial whilst the magnificence distribution is uneven. To calculate the F1-rating, you first want to train your RNN-LSTM

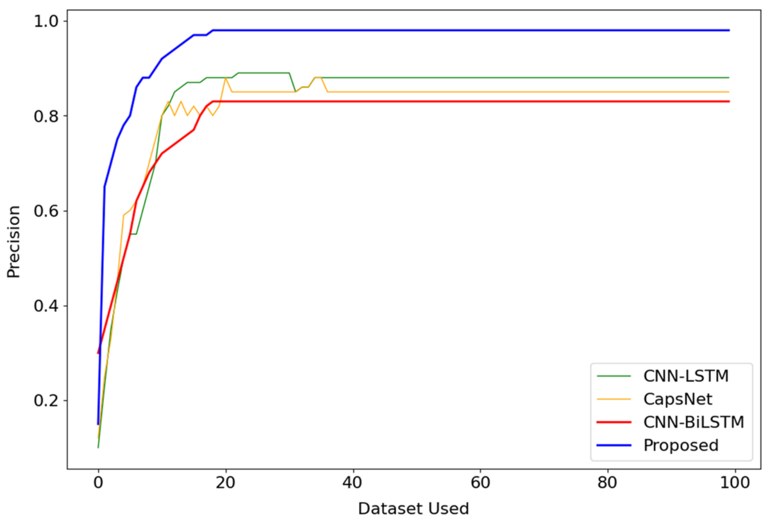

Fig. 4 Evaluation of precision

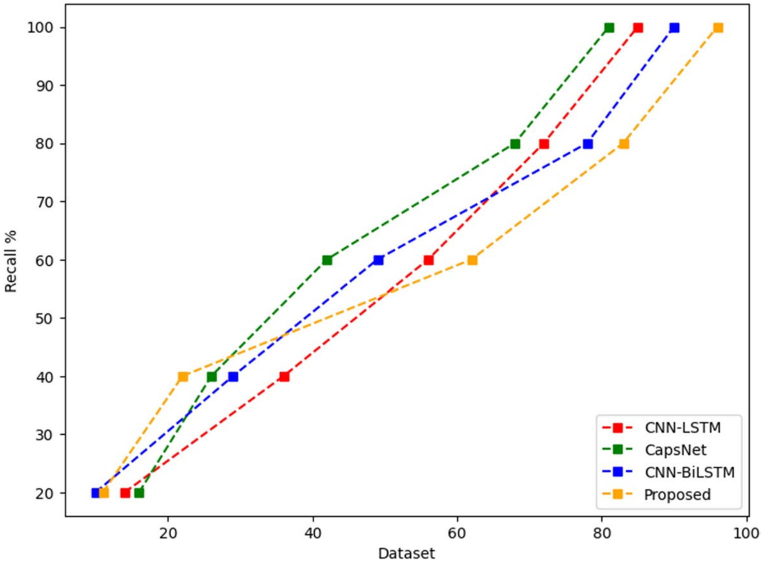

Fig. 5 Evaluation of recall

model in your e-trade dataset after which examine it on a test set to attain the range of true positives (TP), fake positives (FP), and false negatives (FN).

6 Conclusion

The significance of e-commerce trade is growing, and the incorporation of 6G generations into cyber-physical systems (CPS) offers the potential to revolutionize supply chain management. A unique 6G-driven cyber-physical supply chain version is presented in this study, tailored for the e-commerce sector and intended to meet the increasing needs of logistics departments in terms of performance, dependability, and real-time monitoring. Through the integration of 6G capabilities, such as Enhanced Mobile Broadband (eMBB), massive Machine Type Communication (mMTC), and Ultra-Reliable Low Latency Communications (URLLC), these versions provide a comprehensive solution to enhance the performance of the supply chain from manufacturing to delivery. The sequential data from e-commerce cannot be processed by the previous methods. The sequential data is analyzed and predicted in an effective manner for tracking and e-commerce administration in the suggested work. The sequential data is processed and predicted in an effective manner for tracking and e-commerce management in the suggested work. The suggested approach, which is based on a 6G-driven cyberphysical system paradigm, supports the e-commerce industries via the RNN-LSTM method. The adaptive, self-optimizing nature of the suggested approach, which dynamically adapts to changes in call for, deliver circumstances, and network state, is a breakthrough. Adopting this cyber-physical supply chain version powered by 6G ensures significant gains in client satisfaction, sustainability, and operational efficiency. The suggested approach is evaluated against state-of-the-art techniques like CNN-LSTM, CNN-BiLSTM, and CapsNet. The suggested approach improves e-commerce administration and data transmission to enable better decision-making.

Acknowledgements Not applicable.

Author contributions XF: Conceptualization, Methodology, Formal analysis, Validation, Resources, Supervision, Writing—original draft, Writing—review & editing.

Funding Not applicable.

Data Availability The datasets used and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Declarations

Conflict of interest The authors declare that they have no competing interests.

Ethical Approval Not applicable.

Consent for Publication Not applicable.

References

1. Nagy, M., Lăzăroiu, G., & Valaskova, K. (2023). Machine intelligence and autonomous robotic technologies in the corporate context of SMEs: Deep learning and virtual simulation algorithms, cyber-physical production networks, and Industry 4.0-based manufacturing systems. *Applied Sciences, 13*(3), 1681.
2. Kohnová, L., & Salajová, N. (2023). Impact of industry 4.0 on companies: value chain model analysis. *Administrative Sciences, 13*(2), 35.
3. Liu, Y., Tao, X., Li, X., Colombo, A., & Hu, S. (2023). Artificial intelligence in smart logistics cyber-physical systems: state-of-the-arts and potential applications. *IEEE Transactions on Industrial Cyber-Physical Systems*. https://doi.org/10.1109/TICPS.2023.3283230
4. Davis, William, et al. "An innovative blockchain-based traceability framework for industry 4.0 cyber-physical factory."In: *Proceedings of the 2023 5th Asia Pacific Information Technology Conference*. 2023.
5. Cao, K., Wang, B., Ding, H., Lv, L., Tian, J., Hu, H., & Gong, F. (2021). Achieving reliable and secure communications in wireless-powered NOMA systems. *IEEE Transactions on Vehicular Technology, 70*(2), 1978–1983.
6. Liu, J. G. (2021). Data collection in MI-assisted wireless powered underground sensor networks: directions, recent advances, and challenges. *IEEE Communications Magazine, 59*(4), 132–138.
7. Cao, K., Ding, H., Li, W., Lv, L., Gao, M., Gong, F., & Wang, B. (2022). On the ergodic secrecy capacity of intelligent reflecting surface aided wireless powered communication systems. *IEEE Wireless Communications Letters, 11*(11), 2275–2279.
8. Jiang, Y., & Li, X. (2022). Broadband cancellation method in an adaptive co-site interference cancellation system. *International Journal of Electronics, 109*(5), 854–874.
9. Sun, G., Xu, Z., Yu, H., & Chen, X. (2020). Low-latency and resource-efficient service function chaining orchestration in network function virtualization. *IEEE Internet of Things Journal, 7*(7), 5760–5772.
10. Dai, M., Luo, L., Ren, J., Yu, H., & Sun, G. (2022). PSACCF: Prioritized online slice admission control considering fairness in 5G/B5G networks. *IEEE Transactions on Network Science and Engineering, 9*(6), 4101–4114.
11. Abraham, A.; Au, E.; Binotto, A.; Garcia-Hernandez, L.; Marik, V.; Gomez Marmol, F.; Snasel, V.; Strasser, T.I.; Wahlster, W. Industry 4.0: Quo Vadis? Eng. Appl. Artif. Intell. 2020, 87, 85–87.
12. Sun, G., Xu, Z., Yu, H., & Chang, V. (2021). Dynamic network function provisioning to enable network in box for industrial applications. *IEEE Transactions on Industrial Informatics, 17*(10), 7155–7164.
13. Xu, Y., Wang, E., Yang, Y., & Chang, Y. (2022). A unified collaborative representation learning for neural-network based recommender systems. *IEEE Transactions on Knowledge and Data Engineering, 34*(11), 5126–5139.
14. Winkelhaus, S., & Grosse, E. H. (2020). Logistics 4.0: A systematic review towards a new logistics system. *International Journal of Production Research, 58*(1), 18–43.
15. Zheng, W., Lu, S., Cai, Z., Wang, R., Wang, L.,... Yin, L, PAL-BERT: An Improved Question Answering Model. Computer Modeling in Engineering & Sciences,2023.
16. Feng, B., & Ye, Q. (2021). Operations management of smart logistics: A literature review and future research. *Frontiers Engineering Management, 8*(3), 344–355.

17. Liu, X., Zhou, G., Kong, M., Yin, Z., & Li, X. (2023). Developing multi-labelled corpus of twitter short texts: a semi-automatic method. *Systems, 11*(8), 390.
18 Cheng, B., Wang, M., Zhao, S., & Zhai, Z. (2017). Situation-aware dynamic service coordination in an IoT environment. *IEEE/ACM Transactions on Networking, 25*(4), 2082–2095.
19. Li, Q., Lin, H., Tan, X., & Du, S. (2020). Consensus for multiagent-based supply chain systems under switching topology and uncertain demands. *IEEE Transactions on Systems, Man, and Cybernetics: Systems, 50*(12), 4905–4918.
20. Y. Liu et al., "Enhancing input parameter estimation by machine learning for the simulation of large-scale logistics networks," In: Proc. IEEE Winter Simul. Conf., 2020, pp. 608–619.
21. Liu, X., Wang, S., Lu, S., Yin, Z., Li, X., Yin, L., & Zheng, W. (2023). Adapting feature selection algorithms for the classification of chinese texts. *Systems, 11*(9), 483.
22. Hu, F., Qiu, L., Wei, S., Zhou, H., Bathuure, I. A.,... Hu, H, The spatiotemporal evolution of global innovation networks and the changing position of China: a social network analysis based on cooperative patents. R&D Management,2023.
23. Jiang, Z., & Xu, C, Disrupting the Technology Innovation Efficiency of Manufacturing Enterprises Through Digital Technology Promotion: An Evidence of 5G Technology Construction in China. IEEE Transactions on Engineering Management,2023.
24. Sun, L., Liang, T., Sun, X., & Li, C. (2023). & Zhang, C, Temperature self-compensating and high-sensitivity FBG inclination sensor based on the sliding mass principle. *Optical Fiber Technology, 81*, 103539.
25 Dong, L., Hua, Z., Huang, L., Ji, T., Jiang, F., Tan, G., & Zhang, J. (2024). The impacts of live chat on service–product purchase: Evidence from a large online outsourcing platform. *Information & Management, 61*(3), 103931.
26. Zhang, X., Deng, H., Xiong, Z., Liu, Y., Rao, Y., Lyu, Y., Li, Y., Hou, D., & Li, Y. (2024). Secure routing strategy based on attribute-based trust access control in social-aware networks. *Journal of Signal Processing Systems.* https://doi.org/10.1007/s11265-023-01908-1
27. Zhao, L., Qu, S., Xu, H., & Wei, Z. (2024). & Zhang, C, Energy-efficient trajectory design for secure SWIPT systems assisted by UAV-IRS. *Vehicular Communications, 45*, 100725.
28 Xu, X., Liu, W., & Yu, L. (2022). Trajectory prediction for heterogeneous traffic-agents using knowledge correction data-driven model. *Information Sciences, 608*, 375–391.
29. Clayton, E., & Kral, P. (2021). Autonomous driving algorithms and behaviors, sensing and computing technologies, and connected vehicle data in smart transportation networks. *Contemporary Readings in Law and Social Justice, 13*, 9–22.
30. Hu, J., Wu, Y., Li, T., & Ghosh, B. (2019). Consensus control of general linear multiagent systems with antagonistic interactions and communication noises. *IEEE Transactions on Automatic Control, 64*(5), 2122–2127.
31. Chen, B., Hu, J., & Zhao, Y. (2022). Finite-time velocity-free rendezvous control of multiple AUV systems with intermittent communication. *IEEE Transactions on Systems, Man, and Cybernetics: Systems, 52*(10), 6618–6629.
32 Wang, Q., Hu, J., Wu, Y., & Zhao, Y. (2023). Output synchronization of wide-area heterogeneous multi-agent systems over intermittent clustered networks. *Information Sciences, 619*, 263–275.
33. Luo, J., Zhao, C., Chen, Q., & Li, G. (2022). Using deep belief network to construct the agricultural information system based on internet of things. *The Journal of Supercomputing, 78*(1), 379–405.
34. Liu, B., Li, M., Ji, Z., Li, H., & Luo, J. (2024). Intelligent productivity transformation: corporate market demand forecasting with the aid of an AI virtual assistant. *Journal of Organizational and End User Computing (JOEUC), 36*(1), 1–27.
35 Lu, J., & Osorio, C. (2018). A probabilistic traffic-theoretic network loading model suitable for large-scale network analysis. *Transportation Science, 52*(6), 1509–1530.
36 Lyu, T., Xu, H., Zhang, L., & Han, Z. (2024). Source selection and resource allocation in wireless-powered relay networks: an adaptive dynamic programming-based approach. *IEEE Internet of Things Journal, 11*(5), 8973–8988.

Xianyu Fu Chengdu, Sichuan, China, Master of Public Administration, University of Electronic Science and Technology of China. Employed by Sichuan Changjiang Vocational College. Research direction: Electronic commerce.