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Comparison of deep and conventional machine learning models for prediction of one supply chain management distribution cost

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Strategic supply chain management (SCM) is essential for organizations striving to optimize performance and attain their goals. Prediction of supply chain management distribution cost (SCMDC) is one branch of SCM and it's essential for organizations striving to optimize performance and attain their goals. For this purpose, four machine learning algorithms, including random forest (RF), support vector machine (SVM), multilayer perceptron (MLP) and decision tree (DT), along with deep learning using convolutional neural network (CNN), was used to predict and analyze SCMDC. A comprehensive dataset consisting of 180,519 open-source data points was used for analyze and make the structure of each algorithm. Evaluation based on Root Mean Square Error (RMSE) and Correlation coefficient (R2) show the CNN model has high accuracy in SCMDC prediction than other models. The CNN algorithm demonstrated exceptional accuracy on the test dataset, with an RMSE of RMSE of 0.528 and an R2 value of 0.953. Notable advantages of CNNs include automatic learning of hierarchical features, proficiency in capturing spatial and temporal patterns, computational efficiency, robustness to data variations, minimal preprocessing requirements, end-to-end training capability, scalability, and widespread adoption supported by extensive research. These attributes position the CNN algorithm as the preferred choice for precise and reliable SCMDC predictions, especially in scenarios requiring rapid responses and limited computational resources.

Keywords Supply Chain Management (SCM), Decision-making, Machine learning algorithms, Deep learning, Convolutional neural network

Abbreviations

AELM	TiAdaptive extreme learning machineme
ANN	Artificial neural networks
AI	Artificial intelligence
CNN	Convolutional neural network
DL	Deep learning
DRF	Distributed random forest
DT	Decision tree
GBM	Gradient boosting machine
GRU	Gated recurrent unit
KNN	K-nearest neighbors
LR	Logistic regression
LSTM	Long short-term memory
ML	Machine learning
MLP	Multi-layer perceptron

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MRA	Multiple regression analysis
R	Correlation coefficient
RF	Random forest
SCM	Supply chain management
SCMDC	Supply chain management distribution cost
SVM	Support vector machines

Supply Chain Management (SCM) refers to the strategic coordination and management of all activities involved in the sourcing, procurement, production, and distribution of goods and services[1–4]. It encompasses the entire process from the acquisition of raw materials to the delivery of the final product to the consumer[5–8]. The primary objective of SCM is to optimize the flow of products, information, and finances across the supply chain to achieve efficiency, reduce costs, and improve customer satisfaction[9–12]. By integrating and managing the supply chain as a cohesive system, organizations can enhance their competitiveness and responsiveness to market demands, ultimately leading to increased profitability and business performance[12–16].

Despite the advancements in SCM, a significant gap exists in effectively managing and optimizing distribution costs[17–19]. Supply chain management distribution cost (SCMDC) is a critical component of the total supply chain cost, encompassing expenses related to transportation, warehousing, handling, and delivery of products[20,21]. The gap arises from the complexity and variability inherent in supply chain networks, which are influenced by factors such as fluctuating demand, transportation inefficiencies, and dynamic market conditions[22]. Traditional methods of cost estimation often fail to capture these nuances, leading to suboptimal decision-making and increased costs. Closing this gap requires a deeper understanding of the various cost drivers and the development of more sophisticated models that can accurately predict and manage distribution costs in real-time.

In recent years, the integration of advanced machine and deep learning models into SCM and other fields has become increasingly pivotal in addressing the complexities and inefficiencies traditionally associated with distribution cost prediction[23–26]. The sheer volume and diversity of data generated within supply chains, from procurement to delivery, present a significant challenge to conventional analytical approaches, which often fall short in identifying subtle patterns and relationships[27,28]. Machine learning, particularly deep learning, has emerged as a powerful tool capable of processing and analyzing this data to uncover intricate, non-linear relationships between various factors influencing distribution costs[25,29].

This capability not only enhances the accuracy of predictions but also enables more informed and timely decision-making, ultimately leading to better cost management and resource allocation[30,31]. Moreover, the real-time predictive power of machine learning allows organizations to swiftly respond to fluctuations in demand, transportation costs, and other dynamic variables, reducing the risk of bottlenecks and inefficiencies[32,33]. The historical evolution of SCM has seen the development of numerous theories and methodologies aimed at achieving optimal efficiency, yet it is the advent of artificial intelligence that has truly revolutionized the field[34]. Researchers today are increasingly focused on refining these machine learning models, exploring their application across various SCM domains, and pushing the boundaries of what is possible in predictive analytics.

El-Khchine et al. (2018) explored the integration of machine learning techniques like K-Nearest Neighbors (KNN), Logistic Regression (LR), and Support Vector Machines (SVM) with Twitter data to enhance chicken SCM. Their approach identified consumer concerns, facilitating a consumer-centric supply chain design[35]. Bousqaoui et al. (2019) investigated the application of machine learning algorithms in supply chain processes, emphasizing their ability to improve predicting accuracy. They utilized a Long Short-Term Memory (LSTM) model to predict daily demand in a Moroccan supermarket, showcasing the potential of ML in SCM[36]. Islam and Amin (2020) used tree-based machine learning, specifically Distributed Random Forest (RF) and Gradient Boosting Machine (GBM), to predict product backorders in business decision processes. Their ranged approach improved model performance by 20%, offering flexibility and clarity while handling real-time data errors[37]. Alnahhal et al. (2021) utilized linear and logistic regression for dynamic lead-time predicting in make-to-order supply chains. Results showed reasonable accuracy, with an average type I error of 0.07, pioneering optimization in shipment temporal consolidation[38]. Oyewola et al. (2022) aimed to address challenges in supply chain management, such as lead times, bottlenecks, and quality assurance, by classifying supply chain pricing datasets of health medications. They employed deep learning techniques, specifically Long Short-Term Memory (LSTM) and One Dimensional Convolutional Neural Network (1D-CNN), alongside Bayesian optimization and All K Nearest Neighbor (AllkNN). The results demonstrated that the combination of 1D-CNN, AllkNN, and Bayesian optimization outperformed other models, achieving an accuracy range of 61.2836–63.3267%[39]. Al Moteri et al. (2023) aimed to enhance supply chain logistics operations by developing a novel strategy for estimating a macroeconomic index. The method used included multiple regression analysis (MRA) and adaptive extreme learning machine (AELM) models, combined with enhanced genetic algorithms and mathematical modeling. The results showed excellent and stable prediction accuracy, indicating the method's potential usefulness. The conclusion highlighted the approach's promise in improving cost-efficiency and economic value for businesses[40]. Taghiyeh et al. (2023) introduced a novel approach for hierarchical time series predicting in supply chains, leveraging machine learning techniques. By predicting child-level demands independently and then aggregating them, they achieved an 82–90% improvement in predict accuracy compared to traditional methods. This approach promises significant cost reductions in logistics, particularly beneficial for e-commerce operations[41]. Kim et al. (2024) aimed to identify effective machine learning technologies for managing the biodiesel supply chain to reduce operational costs. The study utilized a review of the scientific literature, focusing on various machine learning algorithms. The results highlighted that RF and Artificial Neural Networks (ANN) were the most accurate for predicting feedstock yield, biodiesel productivity, and quality. The conclusion emphasized their utility for engineers and managers in optimizing supply chain operations[42]. Alshurideh et al. (2024) aimed to enhance the transparency and integrity of supply chains by addressing the vulnerabilities of centralized

Supply Chain Management (SCM) systems. The study employed a blockchain-based supply chain management model, integrating Machine Learning (ML) techniques. The results demonstrated significant improvements in product distribution, traceability, partner cooperation, and financing access. The authors concluded that blockchain, combined with ML, can substantially improve SCM performance in the business sector[43]. Amellal et al. (2024) aimed to enhance strategic decision-making in businesses by improving the interpretation of customer sentiment, demand forecasting, and price prediction. The study employed a comprehensive methodology, including the BERT transformer model for sentiment analysis, the Gated Recurrent Unit (GRU) model for demand forecasting, and the Bayesian Network for price prediction. The results indicated superior performance over traditional methods, concluding that this integrative approach provides valuable insights for optimizing pricing strategies and managing supply chain uncertainties[44].

This article discusses a gap in the supply chain field related to shipping and its impact on predicting fluctuations in SCM distribution cost (SCMDC) across various transportation methods by different variables. Its objective is to address this issue by using algorithms, particularly artificial intelligence (AI) and deep learning. The study utilized data from 180,519 open-source datasets and used algorithms such as Random Forest (RF), Support Vector Machine (SVM), Multi-Layer Perceptron (MLP), Decision Tree (DT), and Convolutional Neural Network (CNN) to predict SCMDC of goods (clothing, sports, and electronic supplies), including freight costs and other features (payment type, scheduled shipment day, actual shipment day, late delivery risk, order item discount, order item discount rate, order item profit ratio, order item quantity, order profit per order, shipping mode, sales per customer, and order item product price), for transportation to their destination. Finally, the study compares the efficacy of AI and deep learning algorithms, proposing a method for managing supply chain pricing accordingly.

Methodology

This article uses the conventional algorithms such as RF, SVM, MLP, DT, and the deep learning algorithm such as CNN to predict the SCMDC within the supply chain.

Conventional machine learning

Random forest (RF)

Random Forest (RF) algorithm, a widely utilized and potent technique in machine learning, is used for diverse tasks like classification and prediction[45]. This approach entails amalgamating multiple randomly selected decision trees, whose outcomes are then aggregated to yield the final result[46]. The algorithm operates by first selecting random data samples for each decision tree, which may or may not involve replacement. Subsequently, decision trees are constructed based on these samples and their associated labels. Upon completion, new data samples are introduced to each tree for prediction, and the resulting predictions are combined, often through majority voting or averaging[47]. The model's performance is then assessed using metrics like accuracy and sensitivity. Noteworthy advantages include its robustness against overfitting, enhanced prediction accuracy through result combination, and capability to handle large, high-dimensional datasets. However, drawbacks include increased time and memory requirements compared to standard decision trees, as well as potentially time-consuming parameter configuration[48]. Further details on RF are available in Barjouei et al. (2021)[49]. Figure 1, show the graphical diagram for RF.

Support vector machine (SVM)

Support vector machine (SVM), introduced by Cortes and Vapnik 1995, stands as one of the most impactful machines learning techniques, effectively addressing numerous regression challenges[50]. Its core principle relies

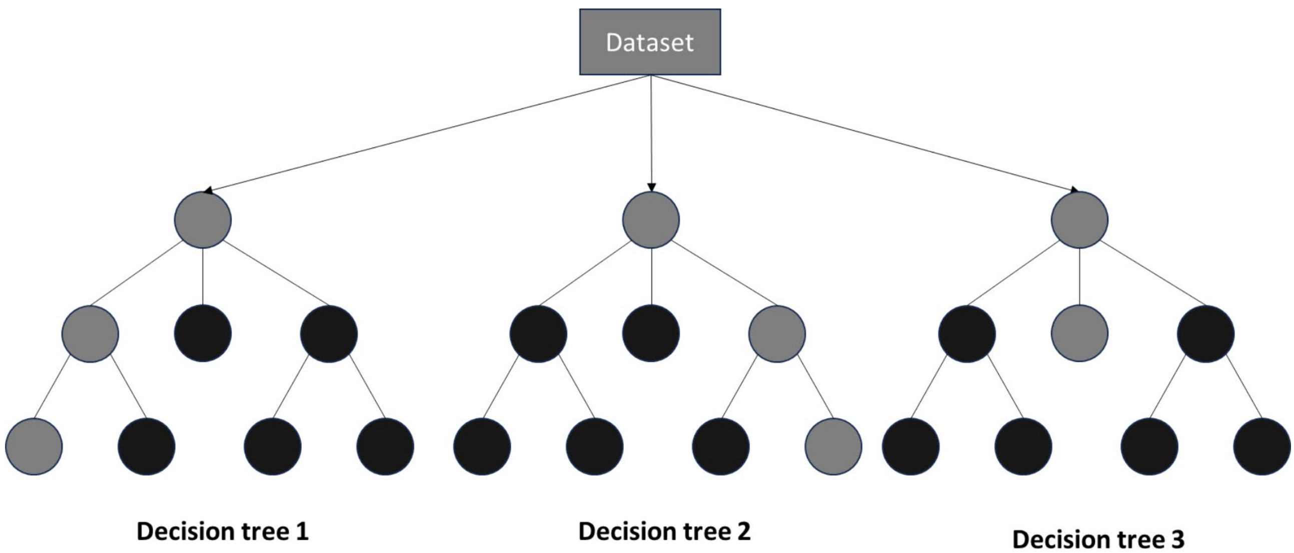

Fig. 1. Block diagram for RF algorithm.

on statistical learning and structural risk minimization to diminish empirical risk and facilitate generalization[51]. The SVM operates by transforming input data nonlinearly into a higher-dimensional feature space, followed by the application of a kernel to tackle linear regression within this transformed space[52]. Further details on SVM are available in Abad et al. (2021)[53]. This study specifically utilizes Polynomial kernels within the SVM framework. Figure 2, show the graphical diagram for SVM.

Multi-layer perceptron (MLP)
The ANN have been extensively utilized since the 1990s[54]. Several factors affect their predictive accuracy, including feature selection, network architecture, transfer functions, and training algorithm choice[55]. The Multilayer Perceptron (MLP) is commonly used due to its adaptability[56]. However, the Levenberg-Marquardt (LM) algorithm used for MLP training may face limitations with complex datasets[57]. Further details on MLP are available in Taud and Mas (2018)[58]. Using more effective optimization algorithms is important for enhancing MLP performance. Sensitivity analysis often recommends a two-hidden-layer structure, with 10 neurons in hidden layer 1 and 5 in hidden layer 2. Transfer functions 'tansig' and 'purelin' are typically chosen for these layers. Figure 3, show the graphical diagram for MLP.

Decision tree (DT)
Decision trees (DT) are renowned as a potent technique used across various domains such as machine learning, image processing, and pattern recognition. This algorithm operates as a hierarchical model, making sequential decisions based on multiple tests conducted on input features[59]. A notable aspect of decision trees is their straightforward structure, facilitating the interpretation of rules and criteria, contrasting with methods like neural networks relying on numerical weights[60]. The primary application of decision trees lies in data mining and information classification and prediction[61]. In this model, each node of the tree embodies certain characteristics

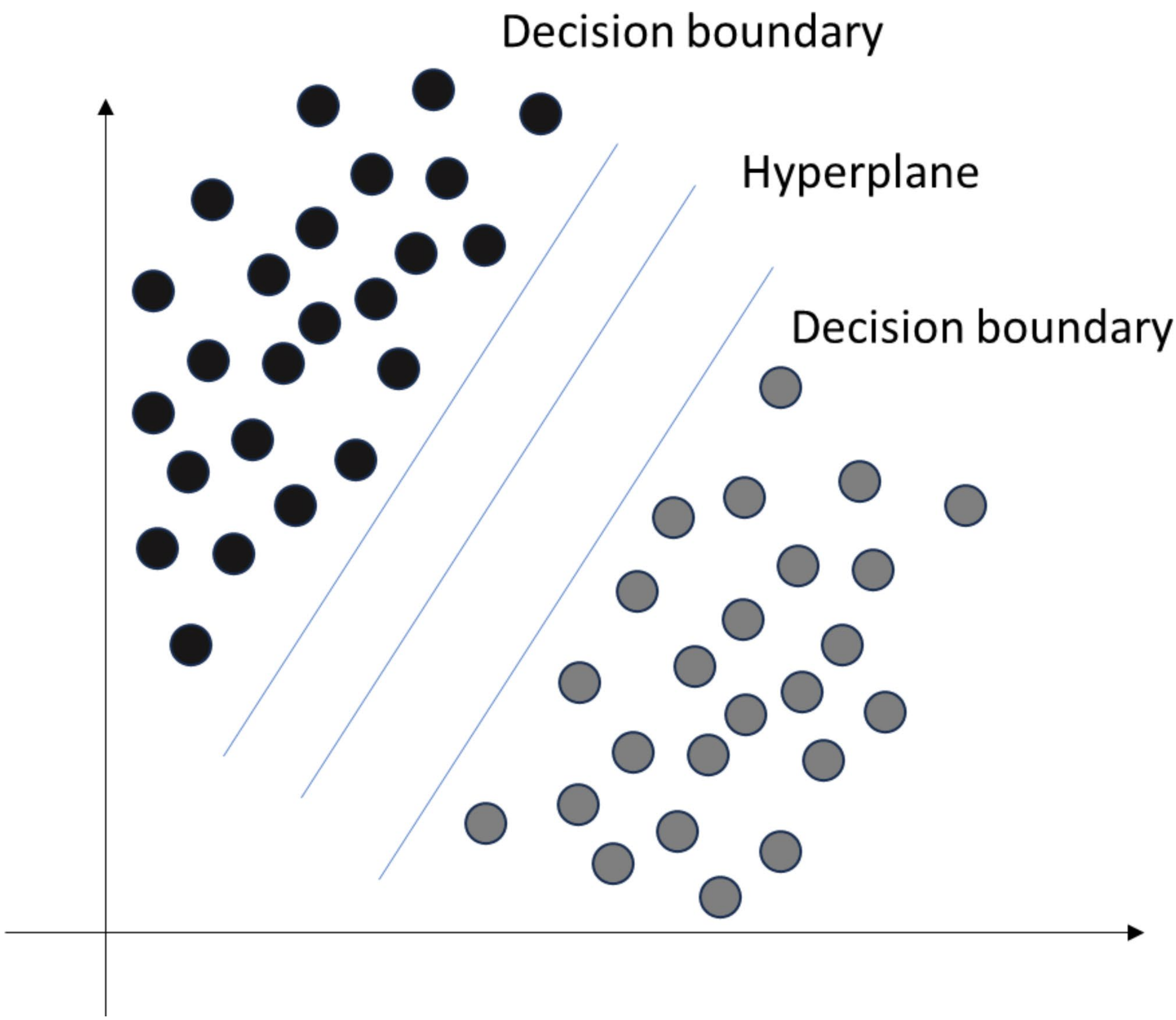

Fig. 2. Block diagram for SVM algorithm.

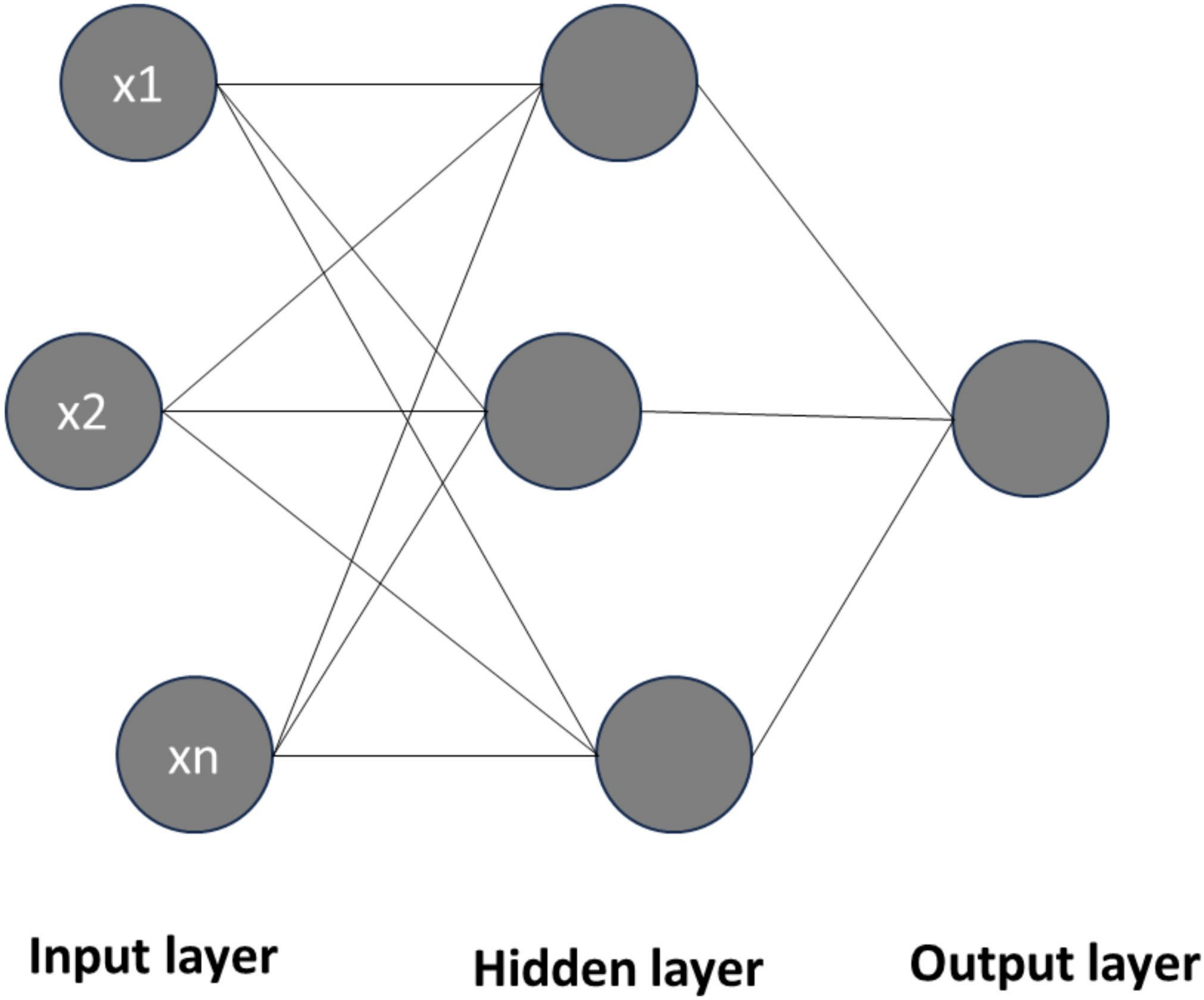

Fig. 3. Block diagram for MLP algorithm.

directly influencing the decision-making process for data classification. By establishing a hierarchical arrangement of nodes and branches, decision trees proficiently analyze complex data. Given their simplicity and accuracy in data analysis, decision trees have garnered attention and find application across diverse domains, including data analysis and classification problem-solving. These algorithms serve as robust and adaptable tools in data analysis. Further details on DT are available in Kamali et al. (2022)[62]. The Fig. 4 diagram below illustrates an example of a decision tree's structure.

Deep learning

Convolutional neural network (CNN)

Convolutional neural networks (CNNs) offer distinct advantages in extracting image features, with parameter sharing serving as the cornerstone for processing input images of diverse sizes[63]. A CNN typically comprises convolution layers, pooling layers, and fully connected layers, with the convolution layer serving as its core[64]. In this layer, the same weight matrix and bias matrix are used to compute inputs across varying positions (Eq. 1):

$$M_{i,j} = \sum\nolimits_{(i-k)(i+k)} \sum\nolimits_{(j-k)(j+k)} (W_{i,n} S_{i,n} + b_{i,n}) \tag{1}$$

where the $M_{i,j}$ is the output factor; $b_{i,n}$, $S_{i,n}$ and $W_{i,n}$ are bais, matrix in specific position and weight of the matrix.

The convolutional process entails sequentially applying the convolution kernel to different locations within the image field, often accompanied by edge-padding operations to ensure dimensional consistency between input and output fields[65]. Compared to conventional fully connected neural networks, utilizing a convolution kernel with shared parameters can streamline model complexity and enhance efficiency[66,67]. Furthermore, using uniform parameters throughout the image field overcomes localized specificity limitations, thereby unveiling hidden rules applicable to each location. Through training, the model dynamically adjusts the convolution kernel's

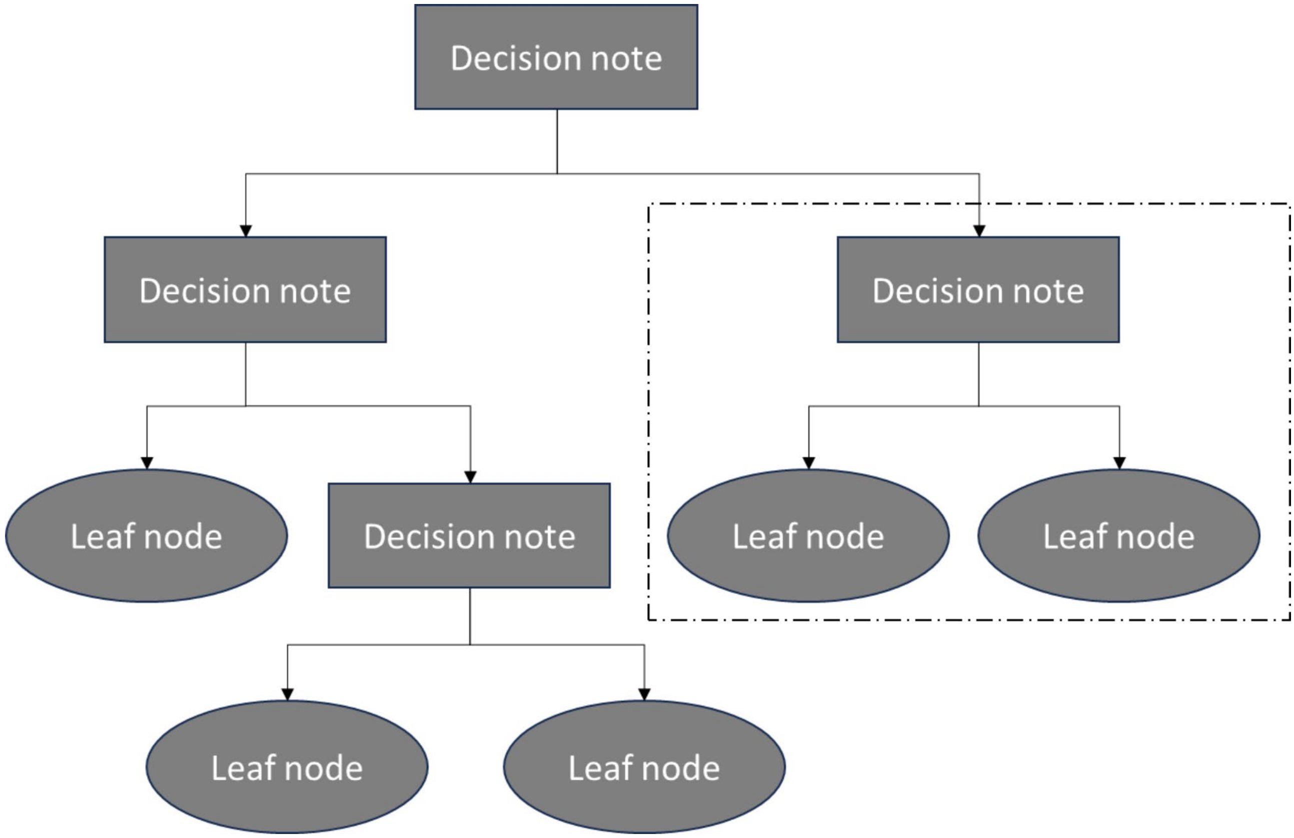

Fig. 4. Block diagram for DT algorithm.

parameters to learn spatial connections, markedly enhancing the model's spatial generalization capability[68,69]. Nonetheless, the convolution process may not be universally applicable to all types of model inputs. Data such as air temperature, cloud cover, and wind speed exhibit relatively stable spatial distributions within a given area, often devoid of spatial distribution monitoring data, and are hence uniformly distributed in space with only temporal variations considered. However, this algorithm demonstrates superior accuracy when handling complex input variables with disparate data distributions[70]. This algorithm boasts numerous advantages, including automated feature extraction, facilitated by CNNs' ability to automatically discern essential features from data without human intervention. Parameter sharing reduces the computational burden by using shared parameters across the network[71]. With the help of pooling layers, CNNs can detect meaningful patterns in variable data based on local features. Additionally, CNNs exhibit robust performance in recognizing intricate patterns and processing large-dimensional images owing to their inherent structural adaptability. Moreover, CNNs showcase flexibility in accommodating various inputs, encompassing images of diverse sizes and dimensions, thereby rendering them applicable to a myriad of problems. Figure 5 for a visual representation of a CNN architecture. The CNN architecture designed with 12 input variables and one output variable includes the following detailed technical specifications: The network begins with an input layer, followed by two convolutional layers with 64, and 128 filters, respectively, each with a 3×3 kernel size and ReLU activation functions. Max-pooling layers with a 2×2 pool size follow each convolutional layer to reduce dimensionality. Batch normalization is applied after each convolution to stabilize learning. The architecture includes dropout layers with a rate of 0.5 after the second convolutional layer and before the fully connected layer to prevent overfitting. A fully connected layer with 256 neurons maps the features to the output, with a softmax activation function applied in the output layer to generate the final prediction. Key hyperparameters include a learning rate of 0.001, a batch size of 32, and a total of 50 epochs for training.

K-mean cross validation
One of the methodologies utilized for data validation involves using the k-fold cross-validation technique, widely recognized as among the most effective approaches[72]. This technique involves treating the dataset as a cohesive entity and segmenting it into multiple subsets. Initially, a portion of the data is earmarked as test data, while the remainder serves as training data[73]. Subsequently, these roles are reversed, with a different subset of data designated as the test set. This iterative process is reiterated for each of the k partitions, typically set at 7 in this context. Generally, the procedure is repeated 10 times, resulting in an average of 70 iterations (Fig. 6).

By using this validation technique, various data analysis challenges are tackled, bolstering the reliability of outcomes while mitigating issues like overfitting and algorithmic inefficiencies in prediction[74]. In this methodology, one subset of data functions as the test set, while the remaining 6 subsets serve as training data.

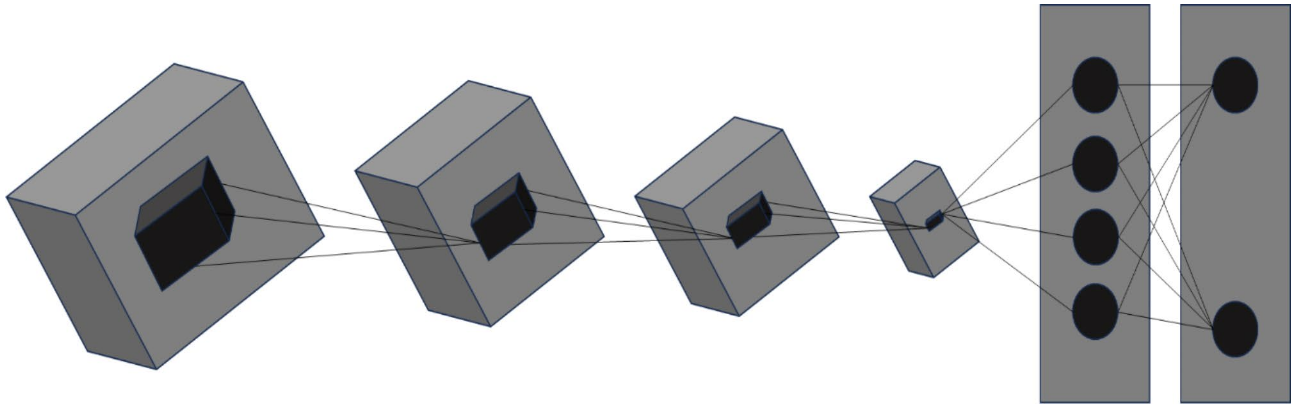

Fig. 5. Block diagram for CNN algorithm.

Ultimately, the average of the minimum values derived from the data serves as the measure of prediction accuracy. This iterative approach substantially contributes to result validation, ensuring the robustness of outcomes.

Discussion of results and comparison methods

The study used data from 180,519 open-source datasets (https://data.mendeley.com/datasets/8gx2fvg2k6/5) and utilized algorithms such as RF, SVM, MLP, DT, and CNN to predict the distribution cost of goods (clothing, sports, and electronic supplies), incorporating factors such as payment type, scheduled shipment day, actual shipment day, late delivery risk, order item discount, order item discount rate, order item profit ratio, order item quantity, order profit per order, shipping mode, sales per customer, and order item product price. Payment types included debit, transfer, and cash, while shipping modes consisted of standard class, first class, second class, and same-day delivery. Table 1 presents statistical analysis for the input variables and predicted SCMDC.

In this article, the prediction of the supply chain concerning SCMDC transportation is explored through the application of deep and machine learning algorithms. A novel approach is undertaken by using a model from the Open Data dataset, representing pioneering work in this area where limited research exists. Thus, this article presents a novelty as artificial intelligence methods have not been previously utilized. Comparing various algorithms for predicting this crucial aspect involves the use of statistical parameters for comparison. To evaluate the machine learning algorithms shown in the Eqs. 2–6.

$$\mathrm{MRE} = \frac{\sum_{\mathrm{i}=1}^{\mathrm{n}} \left(\frac{DC_M - DC_P}{DC_M} \mathrm{x}\ 100\right)_{\mathrm{i}}}{\mathrm{n}} \tag{2}$$

$$\mathrm{MARE} = \frac{\sum_{\mathrm{i}=1}^{\mathrm{n}} \left|\left(\frac{DC_M - DC_P}{DC_M} \mathrm{x}\ 100\right)_{\mathrm{i}}\right|}{\mathrm{n}} \tag{3}$$

$$\mathrm{STD} = \sqrt{\frac{\sum_{\mathrm{i}=1}^{\mathrm{n}} \left(\left(\frac{1}{\mathrm{n}} \sum_{\mathrm{i}=1}^{\mathrm{n}} (DC_{M\mathrm{i}} - DC_{P\mathrm{i}})\right)_{\mathrm{i}} - \left(\frac{1}{\mathrm{n}} \sum_{\mathrm{i}=1}^{\mathrm{n}} (DC_{M\mathrm{i}} - DC_{P\mathrm{i}})\right)\mathrm{mean}\right)^2}{\mathrm{n}-1}} \tag{4}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{n}} \sum_{\mathrm{i}=1}^{\mathrm{n}} (DC - DC_{P\mathrm{i}})^2} \tag{5}$$

$$\mathrm{R}^2 = 1 - \frac{\sum_{\mathrm{i}=1}^{\mathrm{N}} (DC_{P\mathrm{i}} - DC_{M\mathrm{i}})^2}{\sum_{\mathrm{i}=1}^{\mathrm{N}} \left(DC_{P\mathrm{i}} - \frac{\sum_{\mathrm{i}=1}^{\mathrm{n}} DC_{M\mathrm{i}}}{\mathrm{n}}\right)^2} \tag{6}$$

Table 2 presents a comparison of different machine learning (ML) and deep learning (DL) algorithms for SCMDC prediction. This article employs RF, SVM, MLP, DT, and CNN algorithms for this purpose, utilizing 180,519 open-source datasets. 70% of the dataset is allocated for training, 15% for testing, and the remaining 15% for validation. The results obtained guide an analysis of which approach is optimal for predicting product arrival, aiding marketing experts in optimizing product delivery to customers at minimal cost disruptions, thereby enhancing producers' profits.

Based on the data presented in Tables 2, 3 and 4, it is evident that the CNN algorithm outperforms other algorithms in terms of accuracy. Specifically, for the test data detailed in Tables 2, 3 and 4, the MLP algorithm exhibits MRE = 0.004, MARE = 6.328, STD = 8.589, RMSE = 2.715, and $R^2 = 0.880$. Similarly, the DT algorithm shows MRE = 0.009, MARE = 4.004, STD = 6.288, RMSE = 1.871, and $R^2 = 0.888$, the RF algorithm shows MRE = 0.003, MARE = 1.329, STD = 1.675, RMSE = 0.528, and $R^2 = 0.953$ and the SVM algorithm shows MRE=-0.068, MARE = 6.202, STD = 7.836, RMSE = 2.546, and $R^2 = 0.886$. The CNN algorithm also displays MRE=-

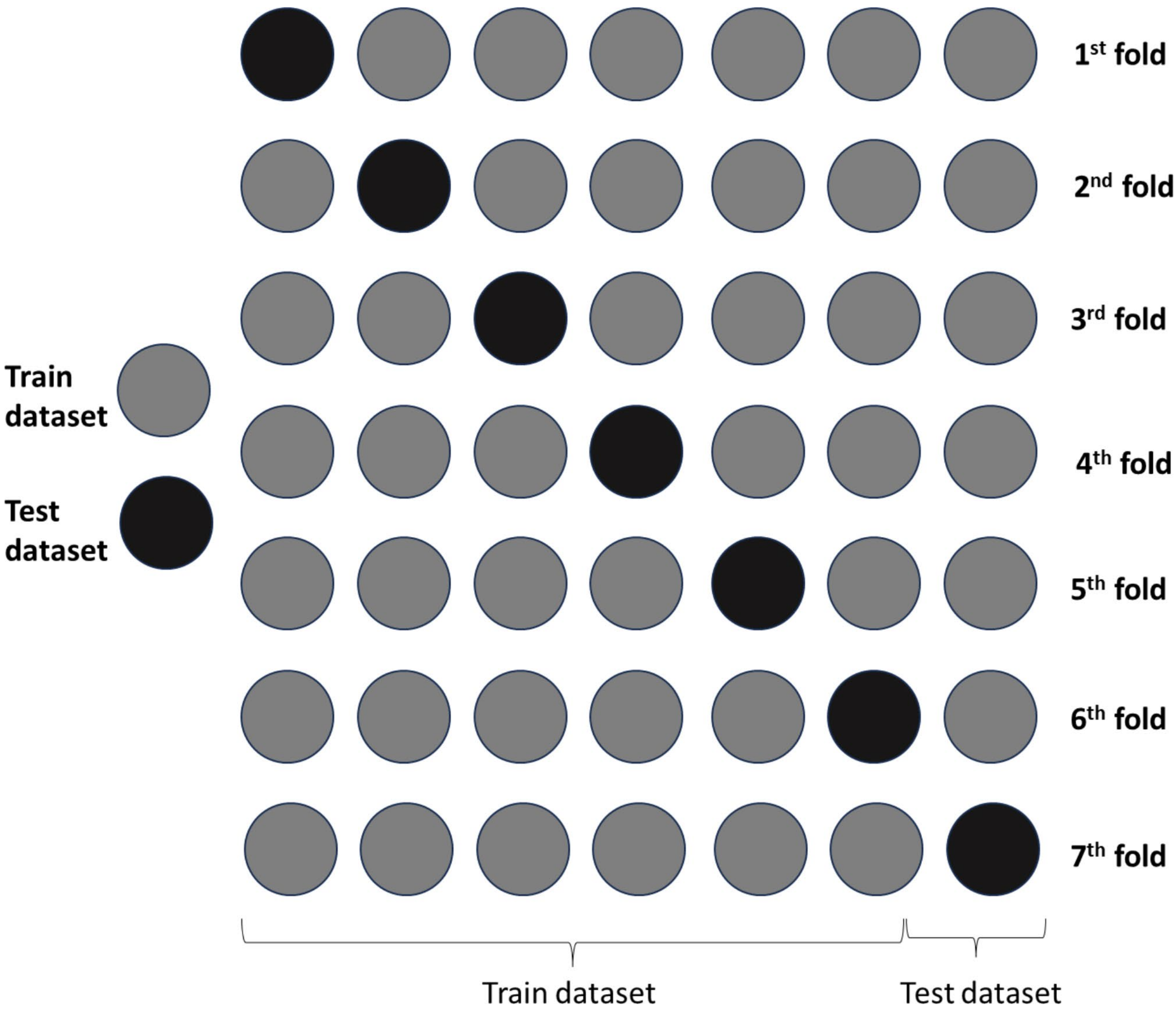

Fig. 6. Block diagram K-fold cross validation.

Parmenter	Min	Max	SD	Ave
Payment's type	0.00	3.00	1.18	1.19
Shipment's day (scheduled)	0.00	4.00	1.37	2.93
Shipment's day (real)	0.00	6.00	1.62	3.50
Late delivery risk	0.00	1.00	0.50	0.55
Order item discount	0.00	500.00	21.80	20.66
Order item discount rate	0.00	0.25	0.07	0.10
Order item profit ratio	-2.75	0.50	0.47	0.12
Order item quantity	1.00	5.00	1.45	2.13
Order profit per order	-4274.98	911.80	104.43	21.97
Shipping mode	0.00	3.00	0.96	0.71
Sales per customer	7.49	1939.99	120.04	183.11
Order item product price	9.99	1999.99	132.27	203.77
Supply chain distribution cost	0.00	500.00	21.80	20.66

Table 1. Statistical analysis for the input/output variables for prediction SCMDC.

Models	MRE	MARE	SD	RMSE	R^2
Units	(%)	(%)	(-)	(-)	(-)
CNN	0.001	1.330	1.677	0.518	0.961
RF	-0.006	4.933	6.715	1.738	0.892
MLP	-0.004	4.940	7.227	1.874	0.885
DT	0.001	3.188	5.367	1.372	0.896
SVM	0.008	4.655	6.952	1.815	0.887

Table 2. Evaluation of error metrics for prediction SCMDC using DL and ML algorithms (RF, SVM, MLP, DT, and CNN) for testing dataset.

Models	MRE	MARE	SD	RMSE	R^2
Units	(%)	(%)	(-)	(-)	(-)
CNN	0.003	1.329	1.675	0.528	0.953
RF	-0.068	6.202	7.836	2.546	0.886
MLP	0.004	6.328	8.589	2.715	0.880
DT	0.009	4.004	6.288	1.871	0.888
SVM	-0.030	5.882	8.166	2.492	0.883

Table 3. Evaluation of error metrics for prediction SCMDC using DL and ML algorithms (RF, SVM, MLP, DT, and CNN) for training dataset.

Models	MRE	MARE	SD	RMSE	R^2
Units	(%)	(%)	(-)	(-)	(-)
CNN	0.003	1.336	1.692	0.517	0.959
RF	0.053	6.830	9.390	2.319	0.890
MLP	0.044	6.791	8.456	2.465	0.884
DT	0.002	4.348	6.217	1.783	0.895
SVM	0.039	6.347	8.050	2.457	0.886

Table 4. Evaluation of error metrics for prediction SCMDC using DL and ML algorithms (RF, SVM, MLP, DT, and CNN) for validation dataset.

0.030, MARE = 5.882, STD = 8.166, RMSE = 2.492, and $R^2 = 0.883$, indicating its superior accuracy compared to the RF, SVM, MLP, DT algorithm, which also presents similar metrics. Consequently, the CNN algorithm proves to have higher accuracy than other artificial intelligence algorithms utilized in this study.

Figure 7 displays a cross-plot illustrating the relationship between predicted and measured data. This visual representation reveals the superior performance of the CNN deep learning algorithm compared to RF, SVM, MLP, and DT machine learning algorithms. Notably, the CNN algorithm achieves an R^2 value of 0.953, indicating a strong correlation between predicted and measured data points. Comparison of R^2 values across algorithms in this study establishes their performance accuracy hierarchy as follows: CNN > DT > RF > SVM > MLP. These findings corroborate earlier observations from Table 2, where the CNN algorithm demonstrated superior predictive capabilities for SCMDC compared to RF, SVM, MLP, and DT algorithms.

Figure 8 visually illustrates the computational error for test data, depicting the error distribution in SWE prediction across RF, SVM, MLP, DT, and CNN algorithms. The plotted coordinates in the figure delineate the error range for each algorithm, with DT, MLP, SVM, RF, and CNN exhibiting error ranges from − 10.4 to 10.5, -17.9 to 17.9, -14.3 to 11.9, -33.2 to 11.5, and − 6.8 to 10.3, respectively. This data illustrates that the CNN model's predictions for test data exhibit a comparatively minor deviation from actual SCMDC values within this range. Consequently, the DT algorithm shows smaller errors, followed by the RF algorithm, while the SVM and MLP algorithms demonstrate larger error ranges. These results reinforce the conclusion that the CNN algorithm surpasses the RF, SVM, MLP, and DT algorithms in SCMDC prediction accuracy, consistently generating predictions with lesser errors and narrower error margins.

Figure 9 illustrates the distribution of prediction errors for the RF, SVM, MLP, DT, and CNN algorithms in SCMDC prediction. Each graph displays error distribution, ideally normal with a mean at zero and relatively low dispersion without significant deviations. These graphs are useful for analyzing algorithm performance and identifying the best one based on error distribution. Closer examination reveals that the CNN algorithm offers superior accuracy compared to others. It is characterized by a smaller standard deviation and narrower dispersion of prediction errors, indicating its more effective data prediction capability. This result demonstrates that the CNN algorithm consistently provides more accurate and reliable predictions for SCMDC. Based on the

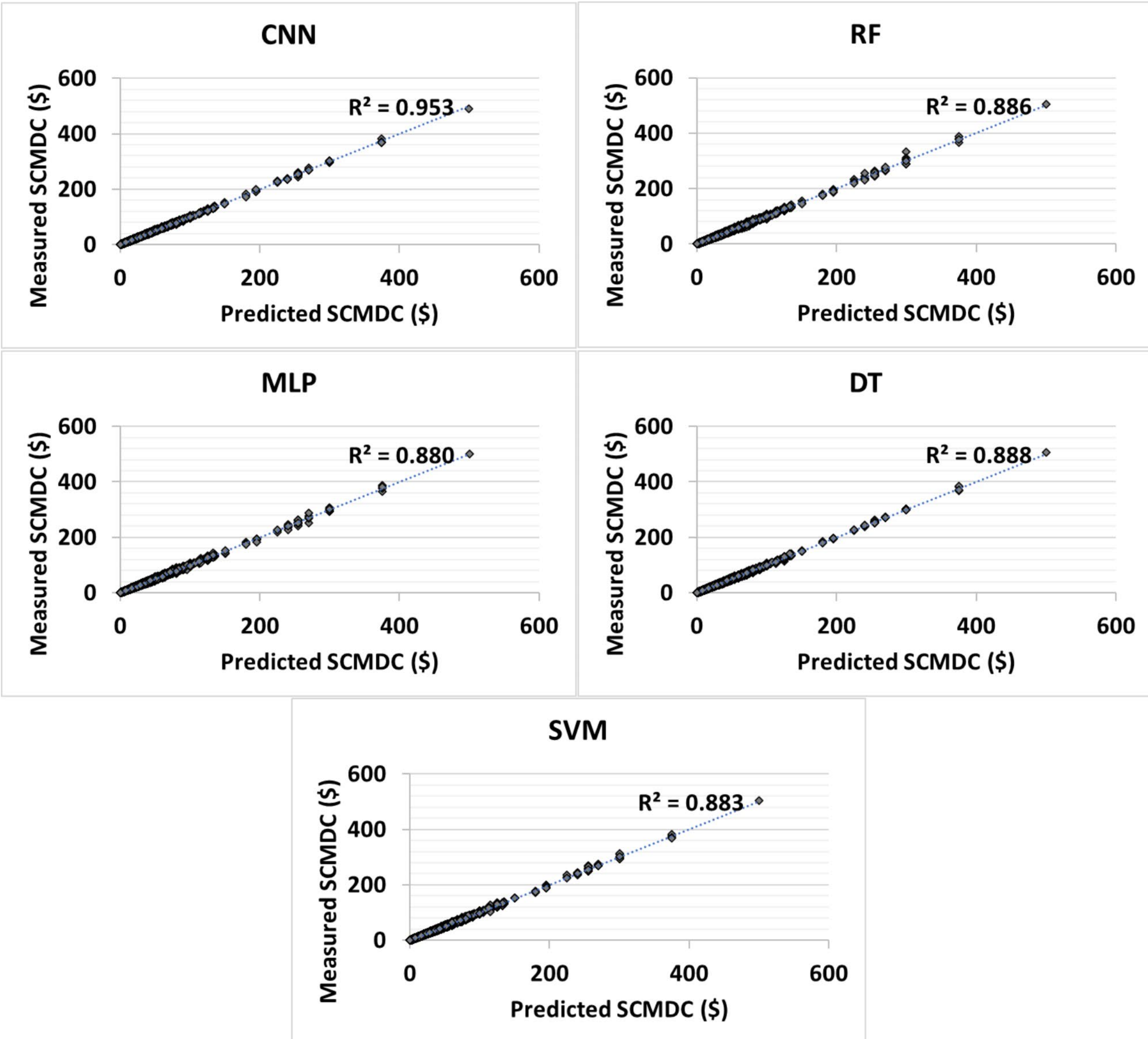

Fig. 7. Cross plot predicting SCMDC using three DL and ML algorithms.

results from Tables 2, 3 and 4 and the analysis of Fig. 9, the algorithms rank in performance accuracy as follows: CNN > DT > RF > SVM > MLP.

The Correlation coefficient (R) assesses the significance of dependent and independent variables in systems like SCMDC models. R ranges from −1 to +1, indicating correlation strength and direction. Values near 1 signify strong positive correlation, near −1 indicate strong negative correlation, and close to zero imply no correlation. Equation 7 computes the efficiency coefficient, quantifying the linear relationship between variables. It aids researchers in gauging the impact of independent variables on output within the SCMDC model.

$$R = \frac{\sum_{i=1}^{n}(T_i - \bar{T})(U_i - \bar{U})}{\sqrt{\sum_{i=1}^{n}(T_i - \bar{T})^2}\sqrt{\sum_{i=1}^{n}(U_i - \bar{U})^2}} \tag{7}$$

A + 1 correlation indicates a perfect positive correlation, implying the most positive effect of independent variables on dependent ones. Conversely, a -1 correlation suggests a complete negative influence of independent variables. Near-zero correlation indicates no significant relationship, implying minimal impact of independent variables on dependents. The coefficient of performance quantifies relationships, assessing the relative importance of independent variables in the SCMDC model. Using the heatmap shown in Fig. 10, a comparison of Pearson's correlation coefficients provides insight into the relationships between the input variables and SCMDC. The results reveal several significant correlations among the variables. Negative correlations are observed with

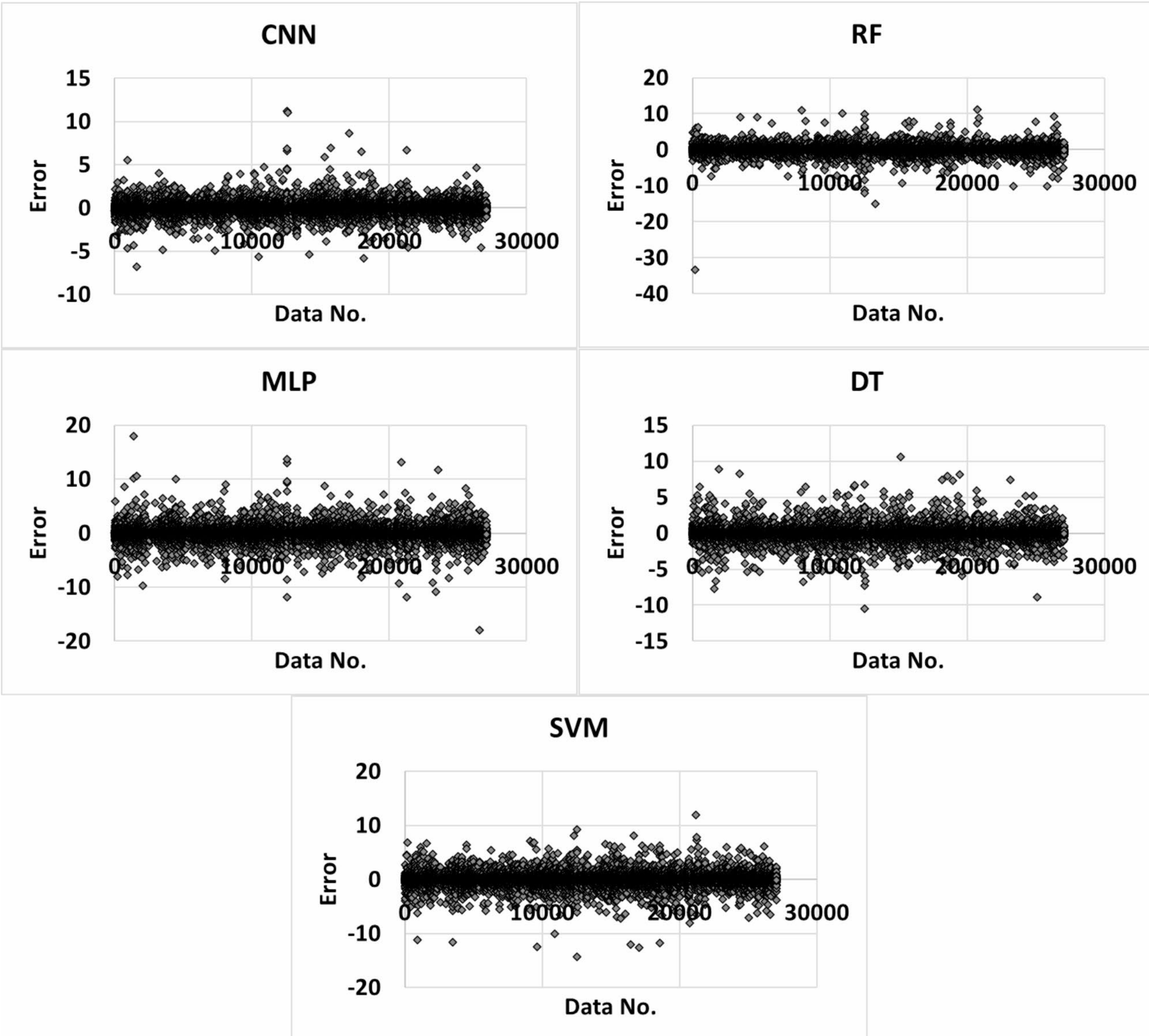

Fig. 8. Error data point based predicting SCMDC using three DL and ML algorithms.

payment type, late delivery risk, order item profit ratio, and shipping mode, indicating an inverse relationship with SCMDC. Conversely, positive correlations are found with the shipment's day (scheduled), shipment's day (real), order item discount, order item discount rate, order item quantity, order profit per order, sales per customer, and order item product price. These variables demonstrate a direct relationship with SCMDC. Notably, the high values of parameters such as order item discount, order item discount rate, sales per customer, and order item product price suggest that these factors have a substantial impact on SCMDC.

While the study effectively demonstrates the superiority of CNN over conventional machine learning models for predicting SCMDC, it also presents some limitations. The research relies heavily on a single dataset, which may not fully capture the variability and complexity of different supply chains. This could limit the generalizability of the findings to other contexts. Although traditional machine learning algorithms such as SVM, RF, MLP, and DT offer robust capabilities for prediction tasks, they present certain limitations when applied to complex datasets like those in SCMDC prediction. These algorithms often require extensive manual feature engineering to perform effectively, which can be time-consuming and may overlook intricate patterns within the data. Additionally, they may struggle with capturing non-linear relationships and interactions between features, leading to less accurate predictions compared to deep learning models like CNNs. Furthermore, conventional algorithms are sometimes less adaptable to the large-scale, high-dimensional datasets typical in SCM, and their performance may degrade as the complexity of the data increases.

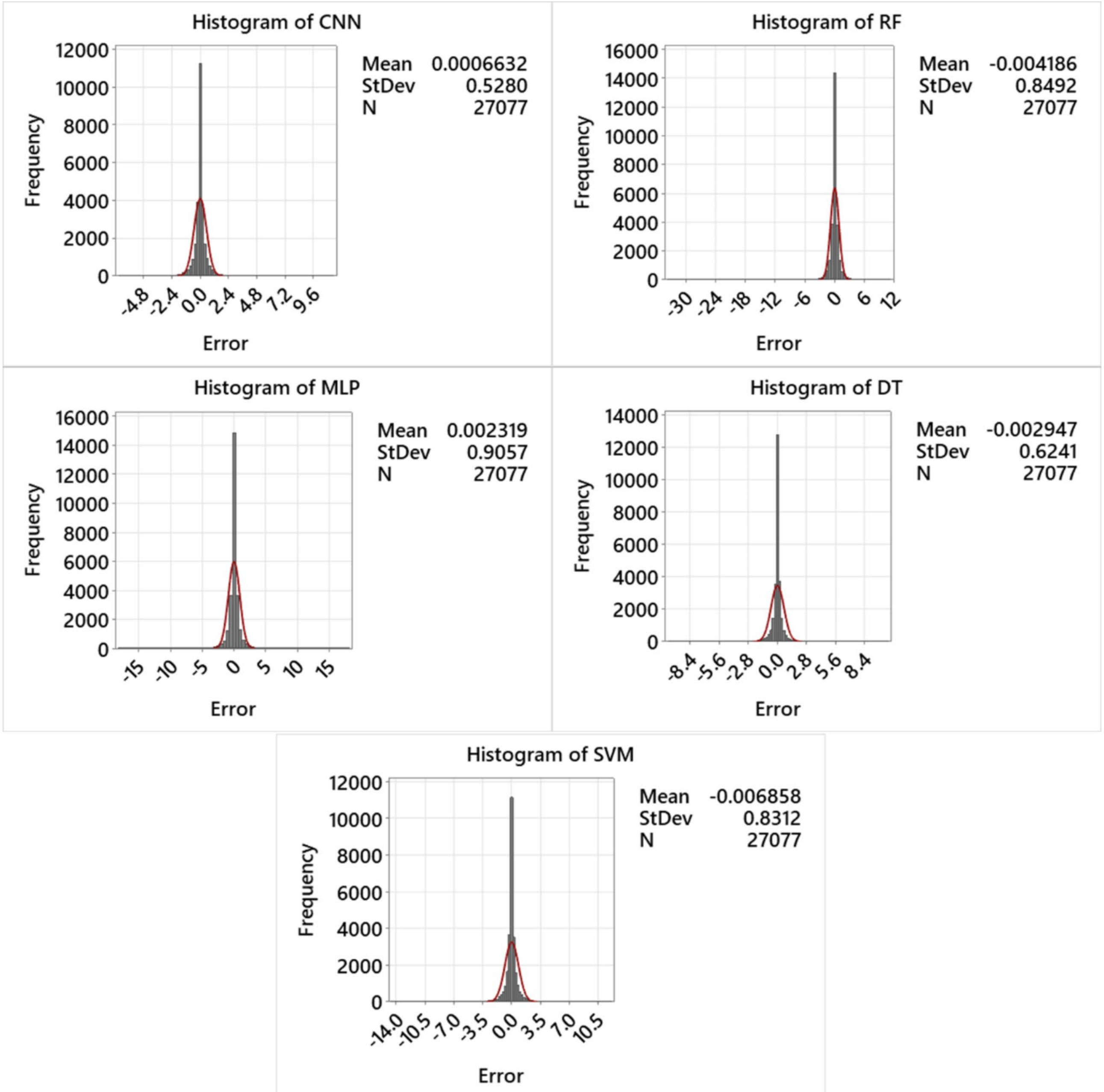

Fig. 9. Error histogram based predicting SCMDC using three DL and ML algorithms.

Recommendations for future scope

Only proofread: Today, Artificial Intelligence (AI) has advanced to the point where it can replace traditional methods and techniques, addressing human challenges in increasingly sophisticated ways. Its progress suggests that AI will become a prominent tool in various fields in the near future. This includes determining and exploring other key techniques and methods that have been discussed in diverse domains, particularly those that could benefit from approaches such as CNN, SVM, RF, MLP, and DT. For example, for future work in the field of supply chain management for future, these AI methods have significant potential for application and comparison like these works[50,52,75–77]. Similarly, they can be beneficial in energy where they might optimize processes and improve efficiency like these works[48,78–81]. Moreover, in electrical engineering, these techniques could be integrated to address complex challenges and enhance system performance like these works[82–86]. In mechanical engineering, a fundamental approach using these methods could offer solutions to problems currently faced by professionals like these works[87–90]. However, it is important to note that solving such complex issues may require substantial time.

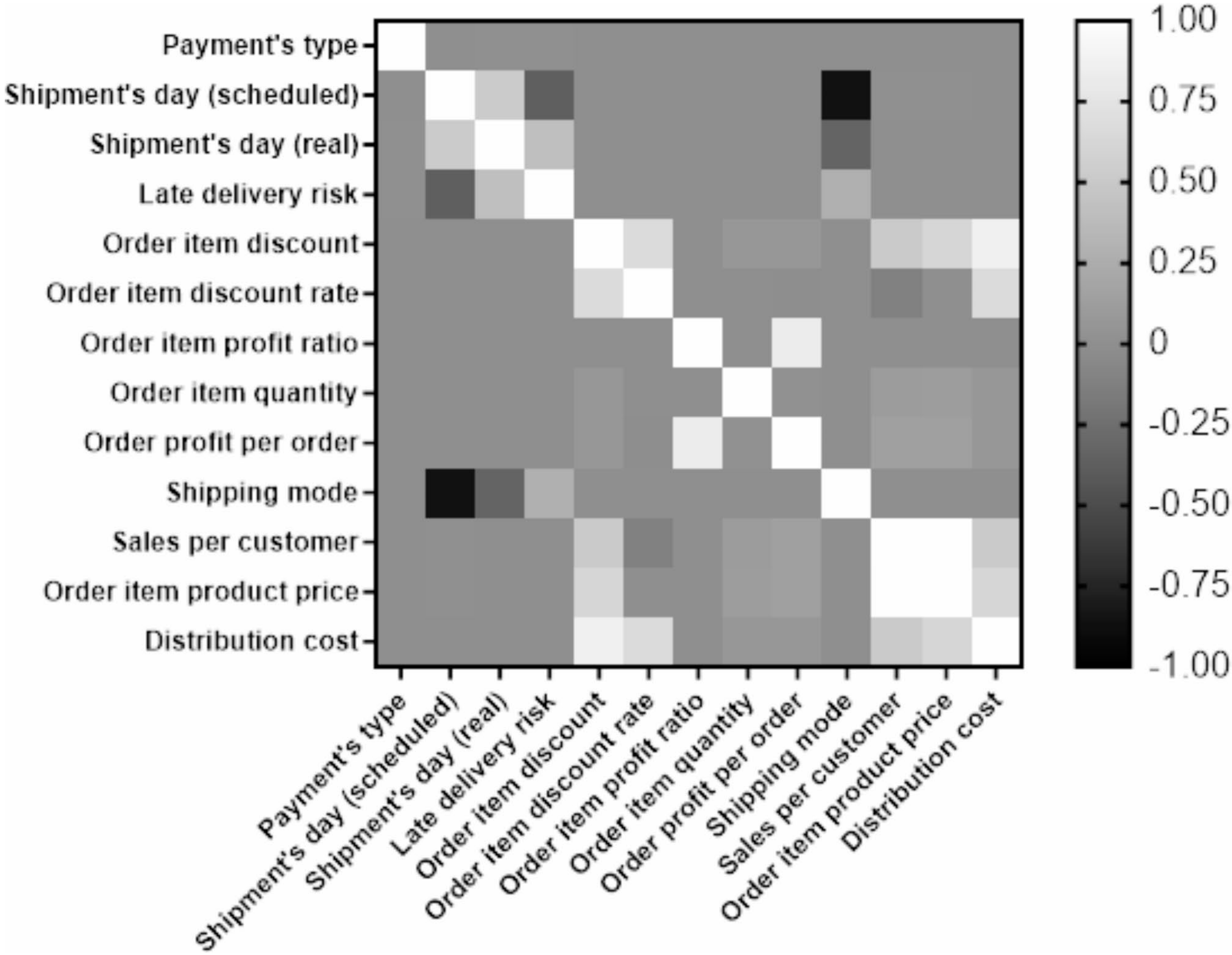

Fig. 10. Heat map block diagram to input/output variables prediction of SCMDC.

Conclusions and recommendations

Supply chain management (SCM) is crucial for achieving organizational success and advancing towards strategic goals. Effective decision-making in financial chain management is essential for analyzing acquired data, reducing supply chain management distribution costs (SCMDC), and maximizing profits. This study aims to improve efficiency and accuracy in SCM through SCMDC forecasting by employing four machine learning algorithms—Random Forest (RF), Support Vector Machine (SVM), Multi-Layer Perceptron (MLP), and Decision Tree (DT)—alongside deep learning with Convolutional Neural Network (CNN). A comprehensive dataset consisting of 180,519 open-source data points was divided into 70% for training, 15% for testing, and 15% for validation. The evaluation of SCMDC prediction performance, based on Root Mean Square Error (RMSE), ranked the models as follows: CNN > DT > RF > SVM > MLP. The CNN model demonstrated exceptional accuracy in SCMDC prediction on the test dataset, achieving an RMSE of 0.528 and an R^2 value of 0.953. CNNs are particularly noted for their robustness and efficiency in handling large datasets, as they can automatically learn hierarchical features, capture spatial and temporal patterns effectively, and maintain computational efficiency through weight sharing. Their ability to handle intricate datasets, minimal preprocessing requirements, and end-to-end training capability make CNNs a superior choice for accurate and reliable SCMDC predictions. Looking forward, future research could explore integrating CNNs with emerging technologies such as real-time data analytics and advanced optimization techniques to further enhance SCM efficiency and adapt to evolving challenges in supply chain dynamics.

To further enhance SCM efficiency, future research should focus on integrating Convolutional Neural Networks (CNNs) with real-time data analytics and advanced optimization techniques. Exploring hybrid models that combine CNNs with reinforcement learning or other AI methodologies could improve adaptability to dynamic supply chain environments. Additionally, incorporating diverse datasets and expanding research to different industry contexts may offer deeper insights and more robust SCMDC prediction capabilities.

Data availability

Data accessible upon academic request from corresponding authors.

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Author contributions

Conceptualization, XY, LT, LL and MS; formal analysis, LT and MS; investigation, XY, LT, LL and MS; methodology, XY and MS; project administration, MS; supervision, MS; software, XY and MS; validation, LT, LL and MS; visualization, MS; funding, LL and MS; writing—original draft preparation, XY, LT, LL and MS; writing—review and editing, XY, LT, LL and MS.

Declarations

Competing interests

The authors declare no competing interests.

Ethical approval

In improve the language of the manuscript, our sole reliance was on the ChatGPT tool, with the authors asserting full authorship and accountability for its entirety.

Consent to participate

All authors are agreeing for participate in this article.

Consent to Publish

All authors are agreeing for the publication of the manuscript.

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