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Optimization Model Construction of Intelligent Identification of Chinese Medicine and Machinery Inventory in Smart Medical Supply Chain Based on Deep Learning

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SUMMARY: *Aiming at the problems of insufficient classification accuracy of production material inventory and difficulty in demand fluctuation prediction of medical device manufacturing enterprises under the background of medical demand growth, this paper takes the medical device inventory in the smart medical supply chain as the research object, and constructs an intelligent inventory identification and prediction model combining ABC-CVA classification and CNN-LSTM deep learning method. The model classifies and identifies inventory materials from two dimensions of capital occupation and production criticality, and then combines the local feature extraction ability of CNN and the time series dependence modeling ability of LSTM to predict the dynamic inventory level of different types of materials. The results show that the overall prediction performance of the constructed CNN-LSTM model is better than that of the baseline model, and it can meet the prediction management requirements of class A high-value materials and CVA critical materials. Under the monthly prediction task, the mean absolute error, root mean square error and symmetric mean absolute percentage error of class B materials are reduced by at least 2.12%, 2.75% and 1.88%, respectively, and the mean absolute error, root mean square error and symmetric mean absolute percentage error of class C materials are reduced by at least 4.15%, 7.38% and 3.65%, respectively. The model can provide data support for medical device manufacturing enterprises to carry out inventory forecasting, dynamic early warning, resource allocation and replenishment decision-making.*

KEYWORDS: *Deep learning; CNN; LSTM; Inventory forecasting; Medical products inventory and medical devices; ABC-CVA classification*

1 Introduction

In the development of the smart medical supply chain, medical products inventory management has become an important research topic in the operation of medical institutions. de Assis et al. pointed out that the management of drugs and materials in hospitals should not be judged solely by capital occupation, but should also incorporate multi-criteria classification methods to identify the management priorities of different materials [1]. Mfizi et al. showed that, after introducing criticality dimensions, the classification results of pharmaceutical inventory could better reflect actual management needs [2]. Yani and Aamer argued that

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forecasting accuracy directly affects the stability and inventory control performance of the pharmaceutical supply chain [3]. Pall et al. demonstrated that machine learning methods can provide effective support for drug shortage prediction and inventory response [4]. Fourkiotis and Tsadiras found that the combination of machine learning and statistical forecasting methods can improve the prediction performance of pharmaceutical sales data [5]. Bertolotti et al. proposed a forecasting framework for drug consumption based on short time series, indicating that data-driven methods have strong application value in pharmaceutical scenarios [6]. de Castro Moraes et al. further pointed out that the hybrid CNN-LSTM structure has clear advantages in capturing temporal dependence and local fluctuation features [7]. These studies provide a useful reference for the application of inventory classification methods and time-series forecasting models to medical products inventory management in this paper.

In this context, the inventory of drugs and medical devices, as the core materials of the medical supply chain, directly affects the efficiency and cost of medical services. Therefore, using data-driven technologies such as deep learning to accurately predict and optimize medical product inventory has become a crucial and urgent problem in the construction of smart medical supply chain.In vitro diagnostic reagent production is characterized by high product diversity, frequent batch switching, and strict production continuity requirements. In this operating environment, inventory management of production materials cannot rely solely on static experience or human judgment. Different materials exhibit heterogeneity in terms of value contribution, supply risk, frequency of use, and criticality of production. Some materials occupy a large proportion of inventory funds, while others directly affect the continuity of critical processes even if their monetary value is low. If these differences are ignored, enterprises will either have excessive inventory, resulting in capital occupation and storage pressure, or shortage of critical materials, resulting in interruption of production scheduling and delay of order delivery. Therefore, the inventory management framework of medical device manufacturers should not only distinguish the management priorities of different materials, but also capture their dynamic change patterns over time. This dual demand explains the necessity of combining inventory classification with time series forecasting in a unified analytical framework. From the perspective of intelligent supply chain management, classification determines which materials need to be monitored preferentially, while prediction provides quantitative support for replenishment time, purchasing intensity, and safety stock adjustment. For companies producing in vitro diagnostic reagents, this combination makes sense because demand is often affected by seasonality, production schedules, downstream order changes, and inventory turnaround cycles. Thus, a model that links management classification to dynamic forecasting can provide a more realistic basis for actual operational inventory control than a single approach based only on accounting indicators or extrapolation of historical trends.

Against the backdrop of the steady improvement of artificial intelligence, many pharmaceutical and medical device enterprises are attempting to transform towards "intelligent management". These enterprises simply believe that "intelligent management" means adding a large number of advanced productivity tools such as automated equipment and robot equipment, without a deep understanding of the industry [8-10]. Pharmaceutical inventory of goods in a variety of categories, the situation of each enterprise is not the same, relying only on the stack of hardware equipment, the lack of intelligent and efficient software system management, it is difficult to achieve the best use of goods, far from reaching the goal of “intelligent management” [11]. And the lack of intra-industry information exchange between different pharmaceutical enterprises, logistics informationization level started late, very low efficiency, high occupancy costs in management, not conducive to the healthy development of the industry. In the process of transformation and upgrading, information

circulation and information control between enterprises involved in intelligent manufacturing is the key to the development of the original inefficient and closed management towards high efficiency, sharing and win-win situation [12-15]. Manufacturing Execution System (MES) [16], Warehouse Management System (WMS) [17], Warehouse Control System (WCS) [18] are the core of the three links. In recent years, manufacturing Execution System (MES) has developed steadily and is widely used in areas with advanced storage systems. It can be used as a real-time information platform for warehouse jobs to support the visualization and coordination of production scheduling information [19]. WMS system is a unified deployment and automation equipment for warehouses. WMS system is the automation equipment in the warehouse for unified deployment and control of the linkage system, is responsible for data communication with the warehouse management system and task processing [20]. WCS serves as the central coordinator between WMS and automated equipment, translating upper-layer instructions into real-time device-level commands while ensuring synchronized information and material flow. Intelligent warehousing systems are inherently complex, involving multi-vendor equipment and heterogeneous protocols. Divergent interpretations of system integration often result in substantial development delays when facilities expand operations, add equipment, or reconfigure workflows.

In this paper, deep learning technology is used to construct an intelligent identification and optimization model of medical products inventory to realize the optimization closed loop of “identification + prediction”, which is divided into the identification and classification link and the inventory prediction link. Specifically, S Pharmaceuticals and Devices Company is selected as a case study, and its in vitro diagnostic reagents are classified by combining the inventory ABC analysis method and CVA management method. Subsequently, CNN and LSTM neural networks were fused to construct a CNN-LSTM medical products inventory prediction model, taking full advantage of CNN's feature information extraction ability and LSTM's sensitivity to time series data. Three evaluation indexes are utilized to compare the prediction performance of different models on the same test set to verify the validity and feasibility of the constructed model, and the CNN-LSTM model is utilized to identify the inventory levels of the four types of medical products inventory to verify the applicability of the constructed model.

2 Intelligent identification optimization model of medical equipment inventory

Supply chain management is an integrated management concept. It enables comprehensive planning by coordinating product flow, information flow, and financial flow within the supply chain, thereby improving overall responsiveness and reducing costs. Inventory management is an important part of supply chain management. For traditional medicine products under the framework of smart supply chain, inventory management mainly focuses on two aspects: inventory structure control and inventory forecasting. The former uses the classification method to classify the inventory items hierarchically, clarify the management priority, and realize the hierarchical control strategy. The latter uses scientific forecasting methods to improve forecasting accuracy and aims to reduce inventory overruns and backorders. On this basis, the deep learning technology is used to construct the intelligent identification and optimization model of medical equipment inventory. The integrated model consists of two key modules: intelligent inventory classification and inventory forecasting, which aims to improve the degree of automation and decision-making accuracy of inventory management through a data-driven approach.

2.1 Classification and management of inventory items

In this paper, S Company is selected as a case to analyze the inventory management problem of its in vitro diagnostic reagent products. S Company is an enterprise engaged in the research and development, production and sales of in vitro diagnostic medical devices. Through the acquisition and prediction analysis of inventory management related data, this study found that Company S still has a large room for optimization in medical device inventory management and inventory level control.

2.1.1 ABC analysis

ABC analysis divides inventory items into three categories (A, B, and C) according to the proportion of stock keeping unit (SKU) funds in the total inventory value. Different levels of control and management are applied to each category.

Category A items require the highest level of control and are characterized by small quantities but high monetary values. Their demand and inventory levels must be monitored in real time. On the premise of ensuring the safety of inventory, the purchase strategy of small batch and frequent order is adopted to reduce the inventory level and minimize the capital occupation. Category B items require daily control and are usually managed through periodic ordering policies, including periodic inventory reviews and fixed quantity purchases based on actual demand. Category C items have a lower level of control, which can reduce the frequency of purchases, make bulk purchases, and simplify inventory management.

2.1.2 CVA management method

The CVA management method, Critical Factor Analysis, is a management method that classifies inventory materials into three to five priorities according to their critical degree of use. The materials with the highest priority are essential to production and business activities, and stockouts are strictly prohibited. Medium priority materials are usually needed in production and operations and are allowed to be out of stock within a certain range or quantity. Lower priority materials are usually easily replaced and stockouts are allowed. Compared with ABC classification, the CVA management method can identify materials that are critical in production and operation activities although they have low monetary value and small quantity. The combination of CVA and ABC method can not only realize the hierarchical management of inventory materials, but also effectively identify the key factors.

2.1.3 Results of the inventory classification

ABC classification mainly reflects the capital occupation degree of inventory materials, while CVA classification law emphasizes the impact of materials on the continuity of production operation. In conventional combination applications, CVA is mostly used as an auxiliary marker on ABC classification results, and does not form an independent category alone. There are differences between the production scenario of in vitro diagnostic reagents and general inventory management. Although the proportion of some materials is not high, once they are out of stock, it often directly affects the production rhythm and scheduling. Based on this actual management requirement, this paper adapted the original classification framework, and set CVA as A parallel and mutually exclusive management category with A, B and C, so as to give this kind of material a higher priority early warning response and scheduling control in the inventory system.

The ABC classification method only considers the proportion of product categories and inventory values, while the CVA classification method considers the influence of key factors. In this paper, the above two methods (ABC-CVA) were combined to classify 200 materials

used in the production of in vitro diagnostic reagents. The total inventory of this batch of materials is 16.58 million yuan. The final classification results are shown in Table 1.

There are 28 types of category A items, accounting for 14.00% of the total inventory SKUs and 70.31% of the total value. These need to be managed centrally, including periodic reviews of requirements and delivery times. Category B consists of 45 project types, accounting for 22.50% of the SKUs and 20.68% of the value, and is managed by general management. Category C includes 116 commodity types, accounting for 58.00% of SKUs, but only 8.24% of values, which simplifies management. The comprehensive analysis identified 11 CVA-critical items, which accounted for 5.50% of SKUs. These resources have an important impact on production and operations and require specialized inventory management strategies different from the ABC category.

Table 1: ABC-CVA classification results of in vitro diagnostic reagent materials

The ABC-CVA category	A	B	C	CVA
Total amount	28	45	116	11
Type proportion(%)	14.00%	22.50%	58.00%	5.50%
Money(10,000 yuan)	1165.68	342.83	136.54	12.95
Money proportion(%)	70.31%	20.68%	8.24%	0.78%

It should be noted that the CVA materials in this paper are not categories generated independently from the ABC classification system, but key materials further identified from the original inventory materials according to the criticality of production and operation. Considering that some materials in the production process of in vitro diagnostic reagents, although the proportion of the amount is not high, once they are out of stock, it will directly affect the production continuity. In this paper, the part of materials are listed separately from the original ABC classification objects in the management display and are controlled independently as CVA categories. Therefore, A, B and C in Table 1 are the classification results after eliminating the key materials of CVA, while CVA is the key materials selected from the scope of the original ABC. The four categories are shown side by side in terms of statistical caliber and do not repeat each other.

2.2 Medical products inventory forecasting model

On the basis of the material classification of in vitro diagnostic reagents completed by enterprise S, the method of Convolutional Neural Network (CNN) and Long Short-Term Memory Network (LSTM) fusion was used to predict the time series of material inventory. An intelligent prediction model of pharmaceutical product inventory based on CNN-LSTM fusion algorithm is constructed.

2.2.1 Convolutional Neural Networks

Convolutional Neural Network (CNN) is a feed-forward neural network with convolutional structure with powerful spatial lattice data processing capability, and its main role is to perform feature extraction on data.

Convolutional neural network mainly includes convolutional layer, pooling layer and fully connected layer. Among them, the convolutional layer plays a key role in feature extraction, and its role is to perform feature extraction on the input multidimensional feature mesh data, extract the weights of the data at different locations by doing inner product of the sliding window data with the convolutional kernel, and get a new matrix, i.e., the feature map. The main work of the pooling layer is to downsample the dimensionality and use the RELU

activation function to ignore some unimportant features and effectively control overfitting. The role of the fully connected layer is to convert the pooled neurons into one-dimensional vector form for further processing and analysis of the data.

2.2.2 Long- and short-term memory networks

Long Short-Term Memory (LSTM) network belongs to a kind of improved recurrent neural network structure for processing sequence data. Compared with the traditional RNN, LSTM network can better solve the gradient vanishing and gradient explosion problems in long sequence data, and is a more mature model in the field of neural networks.

LSTM networks introduce the concept of a "cell state" for storing and transferring information. The cell state can be kept constant throughout the sequence, and the flow of information is controlled by a series of gating mechanisms, which mainly consists of three unique gate structures: forgetting gate, input gate and output gate, and a state module for storing memories.

where C_t is the t moment state information of the LSTM cell, h_t is the t moment output of the hidden layer, and i_t is the t moment input gate, the function is to receive the input x_t of the current moment and the hidden state of the previous moment h_{t-1}, and combine them through a $sigmoid$ function to get a value between 0 and 1 value that indicates how much of the current moment's input information needs to be retained, as shown in Eqs. (1), (2):

$$i_t = sigmoid\left(W_t \cdot \left[h_{t-1}, x_t\right] + b_i\right) \tag{1}$$

$$\tilde{C}_t = \tanh\left(W_c \cdot \left[h_{t-1}, x_t\right] + b_C\right) \tag{2}$$

f_t is a t-moment forgetting gate, which functions to calculate the relationship between the cell state C_{t-1} at the previous moment and the hidden state h_{t-1} at the previous moment using a sigmoid function to obtain a value between 0 and 1 indicating how much information about the cell state at the previous moment needs to be retained as shown in Equation (3):

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

Based on the results of the input gate and the forgetting gate, the cell state C_t at the current moment is updated by adding the input information of the current moment to the cell state and forgetting part of the information of the previous moment. o_t is the t-moment output gate, the function is to use a sigmoid function to calculate the relationship between the input x_t of the current moment and the hidden state h_{t-1} of the previous moment, and get a value between 0 and 1, which indicates how much information of the cell state of the current moment is needed to be output as shown in Eq. (4):

$$o_t = \sigma\left(W_o\left[h_{t-1}, x_t\right] + b_o\right) \tag{4}$$

Calculate the hidden state at the current moment: the LSTM uses the tanh function to calculate the cellular state C_t at the current moment, and obtains a value between -1 and 1,

which denotes the hidden state h_t at the current moment, as shown in Eq. (5):

$$h_t = o_t * \tanh\left(C_t\right) \tag{5}$$

Output result: the LSTM outputs the hidden state $h(t)$ at the current moment to the next layer or as the final output result according to the output gate as shown in equation (6):

$$y_t = W_y h_t + b_y \tag{6}$$

Through these gating mechanisms, the LSTM network can effectively capture the long-term dependencies in the sequence data and can automatically learn a gating strategy suitable for the current task during the training process. The cell state at moment t is updated from C_{t-1} to C_t as shown in Equation (7):

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{7}$$

where W_f, W_t, W_c, W_o, and W_y are the weight matrices corresponding to each module, b_f, b_i, b_C, b_o, and b_y are bias terms, and σ is the *sigmoid* activation function.

2.2.3 CNN-LSTM model construction

CNN's feature extraction through convolution operation has been shown to be equally applicable to time series data analysis and can filter the noisy information in the time series data that is not useful for prediction, thus solving the problem of redundant features introduced by LSTM, whereas using the CNN model alone, although it can perform convolution operation on each time series and well extract the local features in the sequence information, CNN is sensitive to the temporal order of sequence information is not sensitive. Therefore, in this paper, we consider fusing one-dimensional CNN with LSTM to construct a CNN-LSTM model.

The CNN-LSTM fusion model constructed in this paper includes a 1D convolutional layer, a maximum pooling layer, an LSTM layer, and a fully connected layer, totaling four layers.

The CNN part of the model is composed of a one-dimensional convolutional layer and a maximum pooling layer. The 1D convolutional layer traverses the input device inventory information, and uses the convolutional kernel weights to convolve with the local sequence segments of the device inventory information to obtain a preliminary feature matrix that is more expressive than the time series matrix of the original device inventory information. The maximum pooling layer will take the feature matrix computed in the previous convolutional layer as input, slide over the sequence of this matrix with a pooling window, and take the maximum value of the window for pooling every slide to output a more expressive feature matrix.

The whole CNN part can be viewed as a special data preprocessing structure. The convolutional layer extracts the local features on the input medicine inventory data by using the sliding window, while the maximum pooling layer reduces the number of parameters and computation by downsampling the local features, which further improves the generalization ability and training efficiency of the medicine inventory prediction model, and the information of medicine inventory is refined by the CNN part into the input of the LSTM part, which is more sensitive to the time series information. The LSTM layer then models and

integrates local features in the time series direction to extract higher-level feature representations. Finally, the fully-connected layer maps these feature representations to a single output, which outputs the results of the medical products inventory quantity prediction. The overall structure of the CNN-LSTM model for predicting the inventory quantity of medical products inventory instruments in this paper is shown in Fig. 1.

To improve the adaptability of the model to inventory time series prediction, the CNN and LSTM modules are not simply connected in order, but arranged according to the complementary characteristics of local feature extraction and time-dependent learning. In the first stage, a one-dimensional convolutional layer scans the inventory sequence along the time axis, extracting short-range fluctuation patterns—such as sudden rises, temporary drops, and repeated local oscillations—from adjacent observations. The subsequent max-pooling layer compresses the feature maps produced by convolution, retaining only the most representative local responses. This operation reduces redundant noise, constrains the input dimensionality, and alleviates the computational burden of the recurrent modeling that follows. The pooled feature sequences are then fed into an LSTM layer to model temporal dependencies across time steps and capture cumulative effects that local windows alone cannot describe. Finally, a fully connected layer maps the high-level temporal representations learned by the LSTM to quantitative inventory forecasts. This configuration maintains sensitivity to short-term variations while preserving long-range sequential memory, aligning with the nature of medical product inventory, where both recent demand shocks and extended production cycles jointly influence stock levels. Accordingly, the CNN-LSTM architecture adopted here is not a mere sequential stacking of modules, but a task-specific design tailored to inventory sequence modeling.

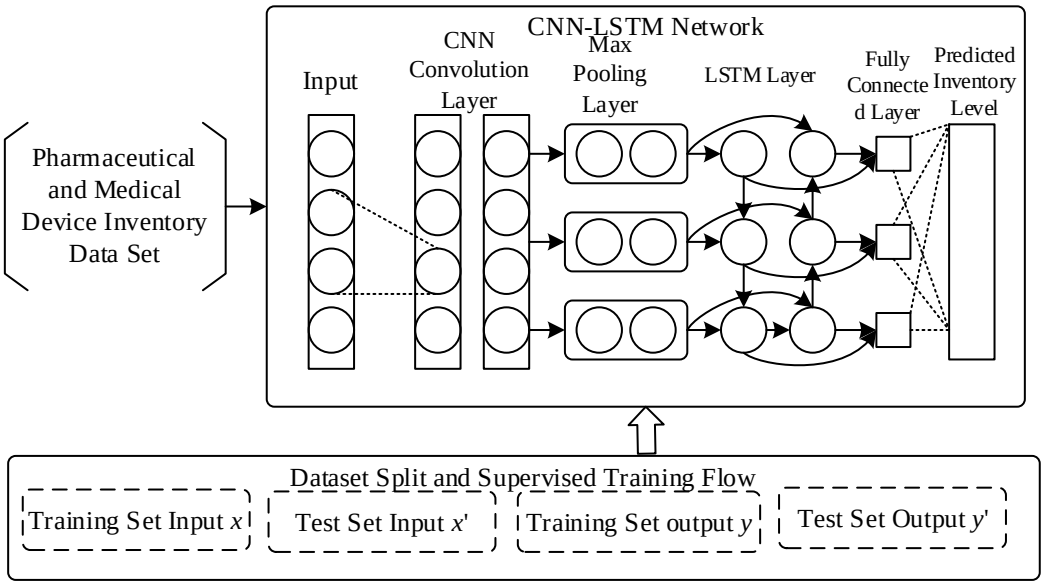

Figure 1: The structure of the CNN-LSTM prediction model

In order to improve the reproducibility of the model training process, this paper further clarifies the specific parameter Settings and sample construction methods of the CNN-LSTM model. The convolution layer adopts a one-dimensional convolution structure, and the convolution kernel size, step size and the number of convolution kernels are determined according to the experimental results. In the pooling layer, max-pooling was used to compress the feature dimension and retain the main fluctuation information. The number of hidden units and Dropout rate of the LSTM layer were used to balance the time series expression ability

and the risk of overfitting. The fully connected layer outputs the single-step inventory prediction results. In the input construction, a sliding window method is used to reorganize the continuous inventory sequence into supervised learning samples, so as to ensure that the model can learn the inventory change law from fixed-length historical observations. At the same time, the key parameters of the baseline model are also adjusted under uniform experimental conditions to ensure that the comparison between different methods is based on a consistent and fair setting.

2.2.4 Correlated Mathematical Expressions

Let $x_t^0 = \{x_1, x_2, ..., x_n\}$ is the input vector of the pharmaceutical inventory volume dataset and n denotes the number of variables. The mathematical expression of the output vector y_{ij}^1 of the convolutional layer is given in equation (8):

$$y_{ij}^1 = \sigma\left(b_j^1 + \sum_{m=1}^{M} w_{m,j}^1 x_{i+m-1,j}^0\right) \tag{8}$$

where y_{ij}^1 is computed based on the output vector x_{ij}^1 of the aforementioned convolutional input layer, b_j^1 denotes the offset of the jth mapped feature, w is the weight of the kernel, m is the index value of the filter, and σ is the ReLU activation function.

The convolutional layer is followed by a pooling layer to link the output feature clusters with the next level, while the pooling layer reduces the number of parameters and networks by decreasing the spatial dimensions, which in turn reduces the computational cost, the maximum pooling for the prediction of medical products inventory is characterized by adopting the maximum value of the previous level, which also has the effect of adjusting the overfitting, and the operation of the maximum pooling layer is shown in Equation (9):

$$y_{ij}^1 = \max_{r \in R} y_{x+i+r,j}^{1-1} \tag{9}$$

The data will enter the LSTM after passing through the CNN input layer and multiple hidden layer outputs, and the LSTM is the successor layer of the CNN in the CNN-LSTM model, whose inputs are the outputs of the CNN layers. Assuming that the input gate of the LSTM cell at stage t is i_t, the forgetting gate is f_t, the output gate is o_t, and the hidden layer state is h_t, the relevant updates of the cell at stage t are shown in Eqs. (10) to (12):

$$i_t = \sigma\left(W_{pi} p_t + W_{hi} h_{t-1} + W_{ci}^o C_{t-1} + b_i\right) \tag{10}$$

$$f_t = \sigma\left(W_{pf} p_t + W_{hf} h_{t-1} + W_{cf}^o C_{t-1} + b_f\right) \tag{11}$$

$$o_t = \sigma\left(W_{po} p_t + W_{ho} h_{t-1} + W_{co}^o C_t + b_o\right) \tag{12}$$

where c_t denotes the state of the cell at the tth stage, σ denotes the activation function, such as the tanh function, which is nonlinear and compresses the input between $[-1,1]$. W is the weight matrix of each gate cell, b is the corresponding offset vector, and p_t denotes the information output of the CNN network containing the key features for the prediction of

the quantity of pharmaceutical inventory at the t th moment after the pooling layer, which is also used as the initial input of the LSTM.

In addition, the updates of LSTM unit state c_t and hidden layer h_t are shown in Eqs. (13) and (14):

$$c_t = f_t^o c_{t-1} + i_t^o \sigma\left(W_{pc} p_t + W_{hc} h_{t-1} + b_c\right) \tag{13}$$

$$h_t = o_t^o \sigma\left(c_t\right) \tag{14}$$

The last layer of the CNN-LSTM model consists of the fully connected layer, which is the output of the feature vector of the LSTM cells that have been "flattened", and let $h^l = \{h_1, h_2, \cdots, h_l\}$, where l is the number of cells of the LSTM. the output of the LSTM is used as the input of the fully connected layer, and the corresponding operation formula of this layer is shown in equation (15):

$$d_i^l = \sum\nolimits_j w_{ji}^{l-1}\left(\sigma\left(h_i^{l-1}\right) + b_i^{l-1}\right) \tag{15}$$

2.2.5 Model Training Steps

After constructing the CNN-LSTM fusion model, the training steps are as follows:

Step1: After normalizing the original inventory data of pharmaceutical and medical device materials to the range of [0,1], the dataset is arranged in chronological order to preserve the temporal dependency of the inventory series. Consistent with the subsequent experimental setting, the records from 2015 to 2022 are used as the training set, the records from 2023 are used as the testing set, and the records from 2024 are used as the validation set. Before training the CNN-LSTM prediction model, the processed inventory data are further reshaped into a three-dimensional format of [number of samples, time steps, number of features], so that different time steps and feature dimensions can be used to obtain the optimal prediction performance of the model.

Step2: During the training process, the convolution kernel window is slid in the direction of the time step to perform convolution operation through the sliding window training mechanism. The RMSE, MAE and SMAPE are taken as the model error values, and the iterative weight update is performed by back-propagating the error information, and the parameters, weights in the convolution kernel and the parameters of the LSTM layer are continuously optimized until convergence, which completes the training of the model.

Step3: In the testing phase, 10% of the test data is used to evaluate the generalization ability of the final trained CNN-LSTM model, here in this chapter, we set to take the prediction results of the CNN-LSTM model with the smallest loss of the validation set in the n runs. Finally, the model is evaluated for its effectiveness in predicting the quantity of medical products inventory.

3 Experimental results and analysis

3.1 Experimental data and evaluation indicators

The experimental data in this paper are from the historical inventory records of materials required for the production of in vitro diagnostic reagents by S Company. Combined with the above ABC-CVA classification results, the research objects are divided into four types of

materials A, B, C and CVA, and the time range covers January 2015 to December 2024. Considering the continuous time-dependent characteristics of inventory changes, the original data are collected and sorted by month before modeling, and the consistency of inventory records of various materials is checked to ensure the uniformity of input samples in statistical caliber and time dimension. In order to reduce the influence of different dimensions and numerical ranges on model training, this paper normalizes the inventory data and compresses each value to the interval [0,1]. Then, according to the input requirements of the CNN-LSTM model, the processed data is reconstructed into a three-dimensional tensor form of [sample number, time step, feature number], so that the convolutional layer can extract local change features, and the LSTM layer can further learn the periodic fluctuations and long-term dependencies of the inventory sequence. The data set division follows the chronological order, in which the data from 2015 to 2022 are used for model training, the data from 2023 are used for testing, and the data from 2024 are used for validation. For time series tasks, chronological splitting is preferred over random partitioning to avoid introducing future information prematurely and to provide a consistent data basis for the analysis of subsequent prediction results.

In order to ensure that the comparison between different methods has a consistent experimental basis, this paper adjusts the parameters of each baseline model, and uniformly adopts the same time sequence division method, input window setting and evaluation index as the CNN-LSTM model. Considering that the original data are monthly inventory records, the sample construction uses a sliding window of length 12 to predict the next month's inventory with 12 consecutive months of inventory observations. XGBoost mainly adjusts the tree depth, learning rate and the number of base learners. RNN, GRU and LSTM mainly adjust the hidden unit size, Dropout rate and training rounds. CNN mainly adjusts the size of convolution kernels, the number of convolution kernels and the pooling window. DARNN mainly adjusts the scale of encoder and decoder and the attention structure, and Prophet combines monthly series features to set the trend, seasonal and change point flexibility parameters. Each deep learning baseline model is trained in a unified experimental environment to reduce the interference of parameter differences on the comparison results.

Based on the four types of in vitro diagnostic reagent materials, A, B, C, and CVA, the relevant inventory data of these four types of materials required for production at S Company from January 2015 to December 2024 are collected as the experimental data of the CNN-LSTM model, in which the data of 2015-2022 are used as the training set, the data of 2023 are used as the testing set, and the data of 2024 are used as the validation set. In order to make it easier to converge to the optimal solution correctly during the model training process and to make the prediction results more accurate, the paper normalizes the data and adopts the method of min-max normalization to compress the range of values to [0, 1].

The commonly used evaluation indexes of prediction models are mean absolute error MAE, mean square error MSE, root mean square error RMSE, mean absolute percentage error MAPE and symmetric mean absolute percentage error SMAPE. When the actual value is zero, MAPE may produce an error due to the denominator being zero, which may happen in the prediction of pharmacy inventories, so this paper selects MAE, RMSE and SMAPE as the measures.

3.2 Experimental results

The testing set selected in this paper is the historical inventory of four types of in vitro diagnostic reagent material from January to December 2023 of S Company. The prediction results of the test set are shown in Table 2 and Figure 2 below. Under the CNN-LSTM inventory quantity prediction identification model, predicted values for the material inventory

test set are closer to the real value, and the prediction effect is more satisfactory. In practice, the production quantity of in vitro diagnostic reagents may be affected by some uncontrollable factors, the results of material inventory identification cannot be completely consistent with the actual results. From the identification results of CNN-LSTM, it can be seen that the fluctuation of the predicted values and the sample values are consistent. The CNN-LSTM model can fit the trend of the change of the stock quantity of material inventory better, and the gap between the predicted data and the real data is smaller in the figure.

Table 2: The forecast storage value of the four products

Month	A (Actual)	A (Predicted)	B (Actual)	B (Predicted)
2023.1	1401	1382	821	832
2023.2	1112	1129	961	947
2023.3	1284	1267	857	845
2023.4	1078	1091	898	912
2023.5	1191	1207	891	879
2023.6	1342	1320	860	871
2023.7	1461	1480	923	909
2023.8	1254	1236	839	851
2023.9	1528	1547	783	771
2023.10	1322	1305	804	791
2023.11	1427	1446	806	819
2023.12	1598	1616	852	840

Figs. 2(a) to 2(d) show the columnar comparison results of actual values and predicted values for class A, class B, class C and CVA materials in the 2023 test phase, respectively. Overall, the predicted inventory values of the four types of materials maintain a high consistency with the actual inventory values in the monthly change trend, indicating that the CNN-LSTM model can better capture the time series characteristics of inventory fluctuations of different types of materials. Among them, the change performance of class A material in high value months and low value months is more obvious, and the prediction results are in good agreement with the fluctuation trend. The fluctuation of class B materials is relatively stable throughout the year, and the predicted value and the actual value remain close in most months. Although there is a small deviation in some months for class C materials, the overall change direction is consistent with no obvious distortion. The prediction results of CVA materials can also reflect the rise and fall of actual inventory. Synthesizing the comparison results of the four types of materials, it can be seen that the difference between the model output and the real inventory is small, which can provide more reliable data support for subsequent inventory analysis and management decisions.

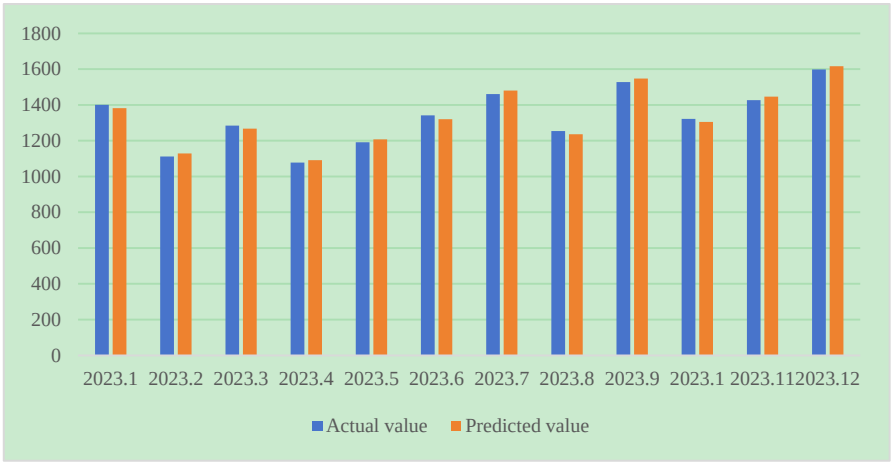

Figure 2: (a) Actual vs. predicted inventory of Category A materials in 2023

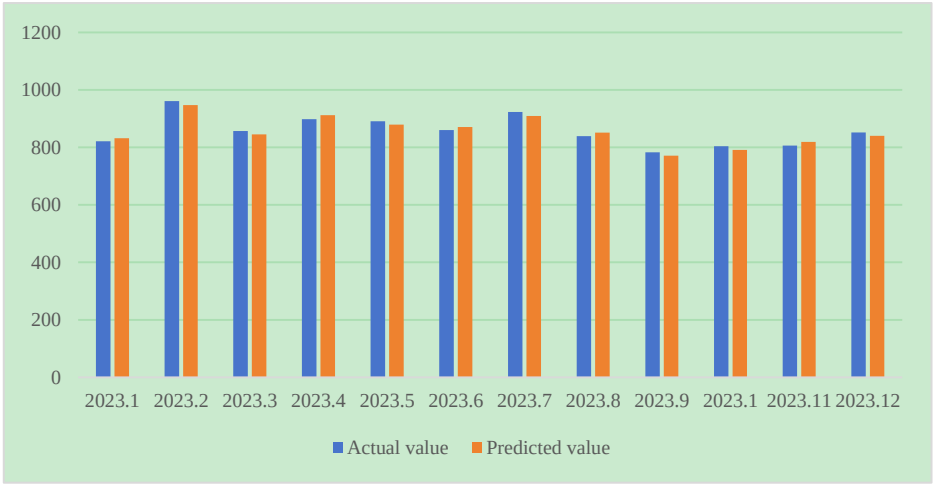

Figure 2: (b) Actual vs. predicted inventory of Category B materials in 2023

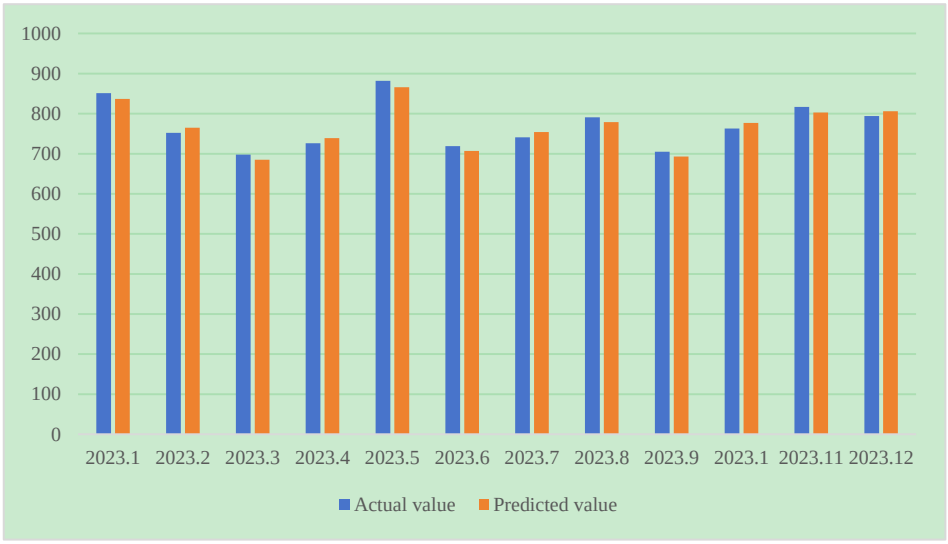

Figure 2: (c) Actual vs. predicted inventory of Category C materials in 2023

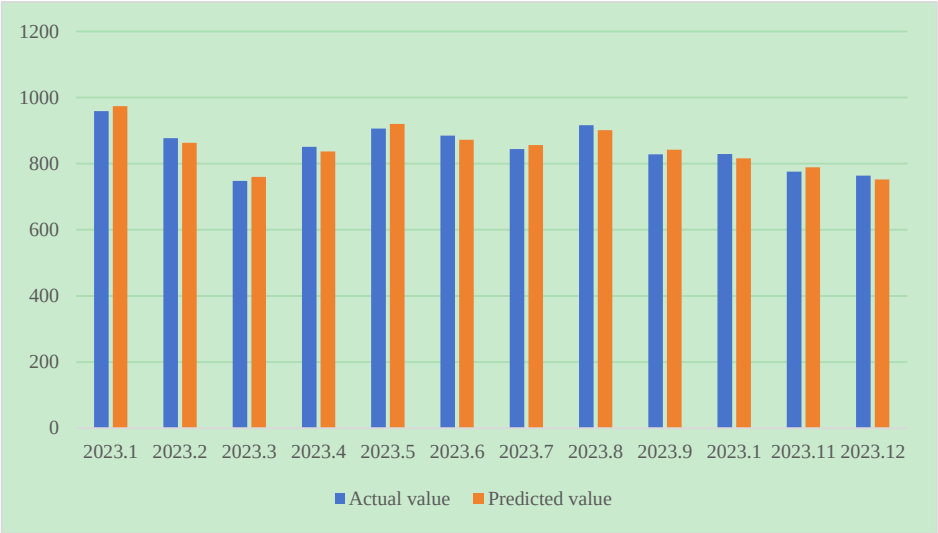

Figure 2: (d) Actual vs. predicted inventory of Category CVA materials in 2023

3.3 Comparative experiments

To ensure consistency with the monthly inventory records used in this study, three forecasting levels were examined in the contrast experiment, including 1, 2, and 3 month forecasting tasks. The proposed CNN-LSTM model is further compared with several baseline methods. Since Class B and class C materials have representative inventory fluctuation patterns, their inventory levels are selected as the prediction targets for comparative analysis. The benchmark methods include XGBoost, GRU, Prophet, RNN, LSTM, CNN, and DARNN.

The performance comparison of the Class B material inventory prediction task is shown in Fig. 3, where (a)~(c) denote the results of MAE, RMSE, and SMAPE metrics, respectively. For Category B materials, when the length of the prediction task is taken as 1 month, the MAE, RMSE and SMAPE of the CNN-LSTM model achieve the best results, which are 2.12%, 2.75% and 1.88% lower than the next best model, and when short-term prediction is carried out, the model is able to fully explore the implied change rules of the material inventory data, and it has a high accuracy rate. when the length of the prediction task is taken as 2 months, the MAE, RMSE and SMAPE of the CNN-LSTM model are reduced by 1.35%, 0.83% and 1.24% for the suboptimal model, and the accuracy of the model decreases when the prediction task becomes longer. when the length of the prediction task is 3 months, the MAE, RMSE, and SMAPE of the CNN-LSTM model decrease by 1.06%, 0.72%, and 1.03% compared to the next-best model, and at this point the model prediction and identification accuracy further decreases because the model uses less data for prediction than the length of the prediction target, and the ability to capture the time-series trend is weakened, and the CNN-LSTM model in the test set overall performance is better than the baseline model.

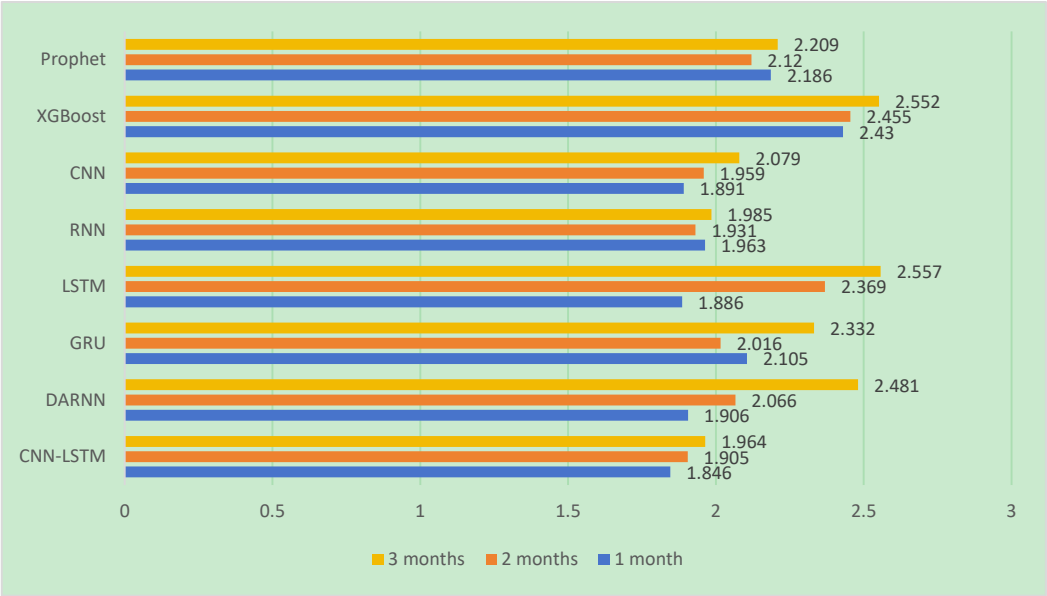

Figure 3: (a) MAE comparison of inventory forecasting for Class B materials under 1-, 2-, and 3-month forecasting tasks

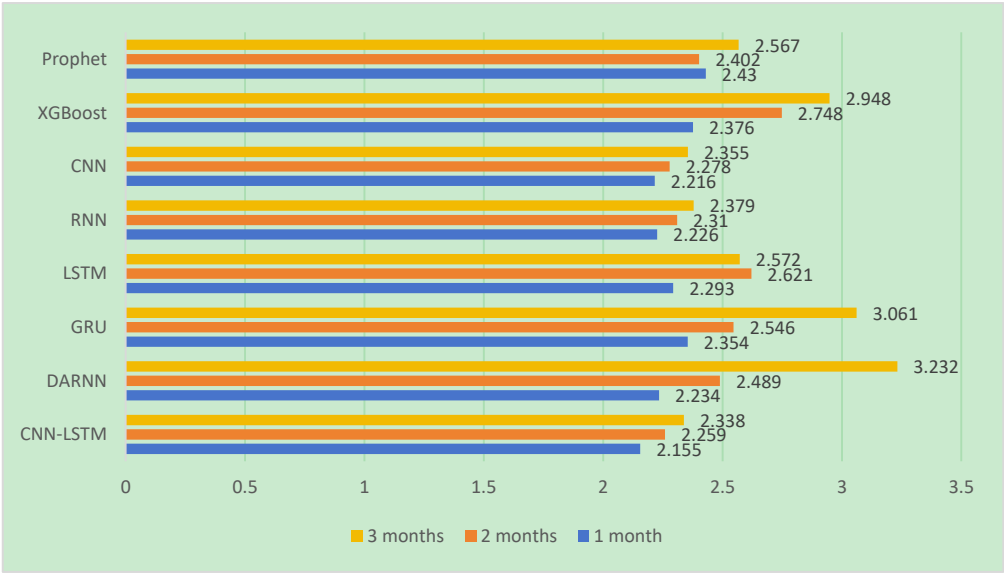

Figure 3: (b) RMSE comparison of inventory forecasting for Class B materials under 1-, 2-, and 3-month forecasting tasks

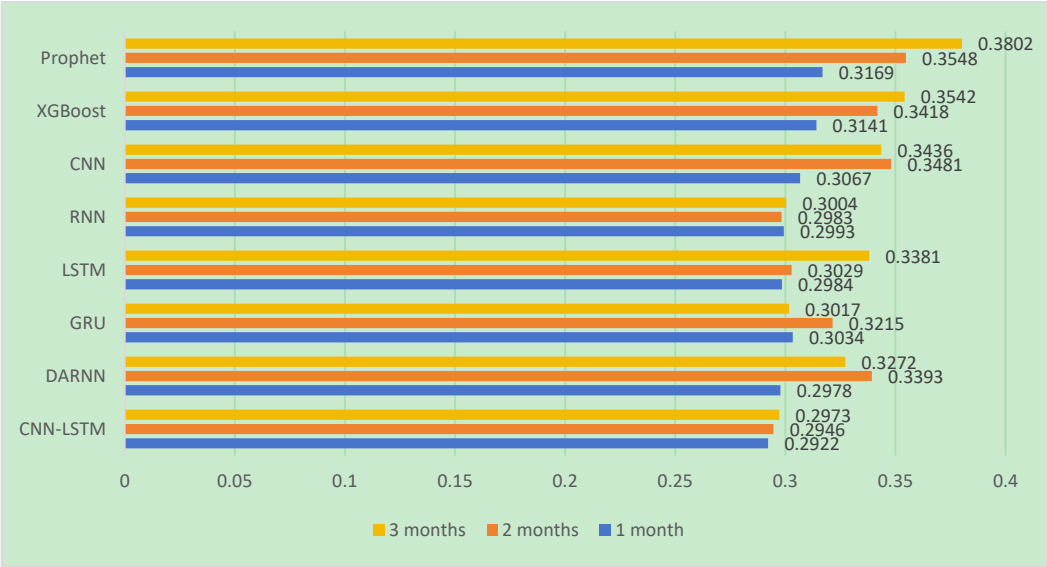

Figure 3: (c) SMAPE comparison of inventory forecasting for Class B materials under 1-, 2-, and 3-month forecasting tasks

The performance comparison of the inventory prediction task for class C materials is shown in Fig. 4. Taking the inventory of class C materials as the prediction and identification target, the CNN-LSTM model achieves the best results of MAE, RMSE and SMAPE reduced by 4.15%, 7.38% and 3.65% compared to the next best model when the prediction length is 1 month. At a prediction task of 2 months, the MAE, RMSE and SMAPE of this paper's model were reduced by 3.21%, 6.13% and 3.36% compared to the next best model. At a prediction task length of 3 months, the MAE, RMSE and SMAPE of the CNN-LSTM model were reduced by 2.62%, 5.34% and 2.91% compared to the next best model. The results of predictive identification of two types of material inventories showed that the CNN-LSTM model was able to make accurate predictions of material inventories for the next one to three months, thus enabling the model to have high prediction accuracies under both short-term and long-term prediction tasks.

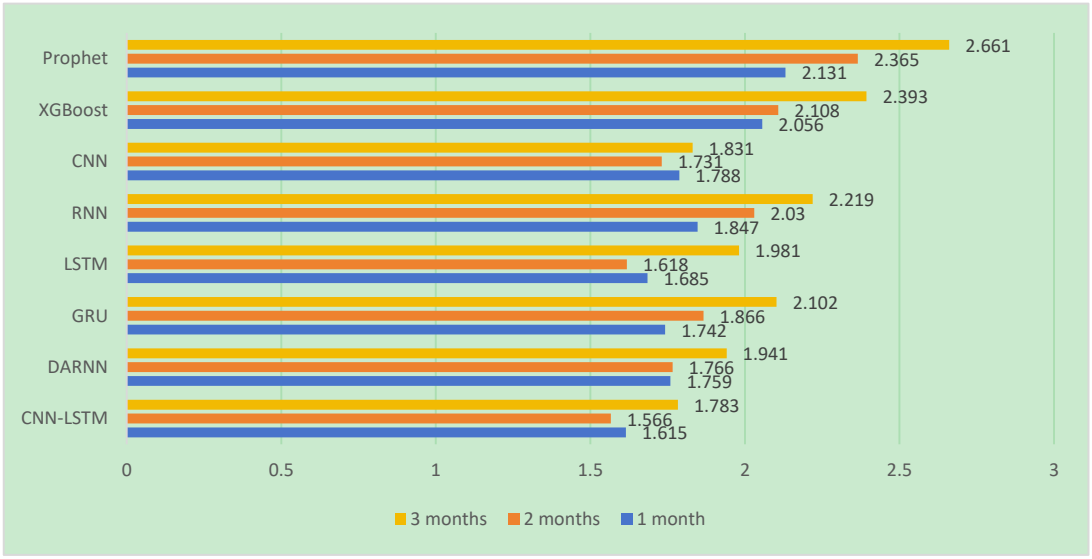

Figure 4: (a) MAE comparison of inventory forecasting for Class C materials under 1-, 2-, and 3-month forecasting tasks

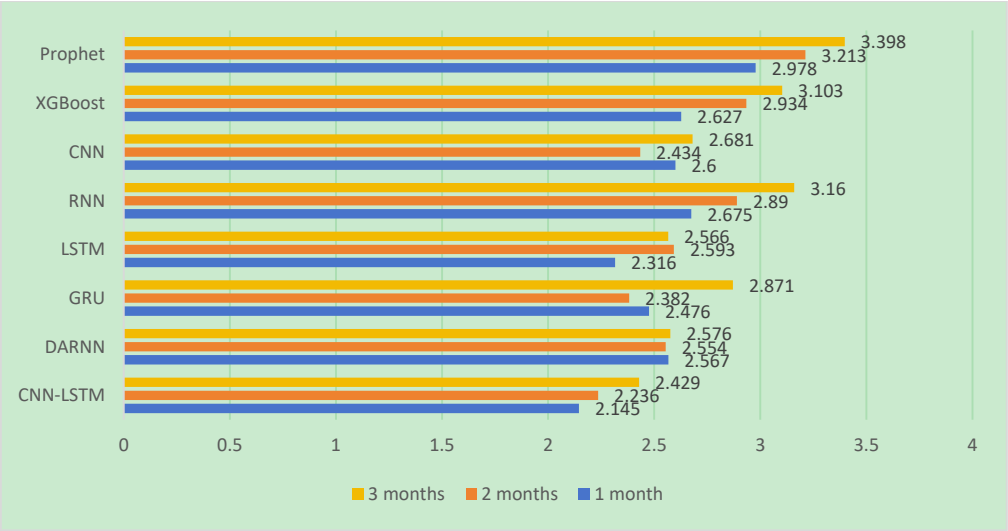

Figure 4: (b) RMSE comparison of inventory forecasting for Class C materials under 1-, 2-, and 3-month forecasting tasks

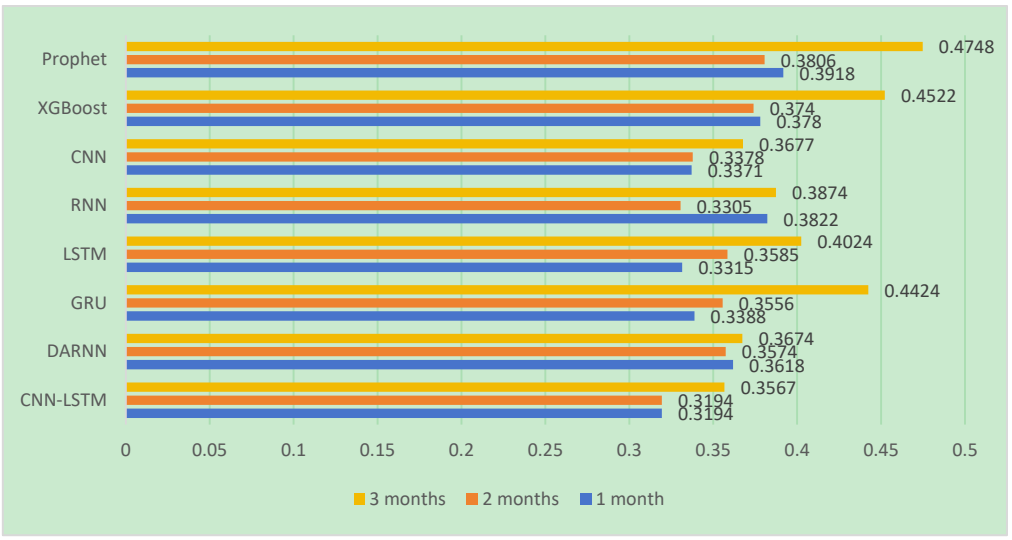

Figure 4: (c) SMAPE comparison of inventory forecasting for Class C materials under 1-, 2-, and 3-month forecasting tasks

3.4 Medical products inventory and medical devices forecast results

In this study, material "identification" and inventory "prediction" correspond to two different links, respectively. The former is completed by ABC-CVA comprehensive classification, which is used to determine the management category of in vitro diagnostic reagent production materials. The latter is completed by the CNN-LSTM model to calculate the inventory quantity at the future time point. Based on the historical inventory series of four types of materials of enterprise S, this paper forecasts the inventory level in December 2024, and the results are shown in Table 3. The prediction results show that the predicted inventory values of class A, B, C and CVA materials in December 2024 are 1331, 879, 747 and 736, respectively. The above results reflect the predicted quantities of four types of materials at the category level, which are used to describe the overall inventory status under different management categories, rather than the detailed predicted values of individual SKUs.

In order to test the usability of the model output in the business scenario, this paper

imports the prediction results in Table 3 into the existing inventory management process of enterprise S and compares them with the preset safety stock threshold. The comparison results can provide a basis for the adjustment of procurement plan, the arrangement of replenishment rhythm and the early warning of key materials, so that the prediction results can be used in the subsequent inventory decision-making process. Table 3 presents the class-level prediction results for materials A, B, C, and CVA in December 2024, and Figure 5 presents the SKU-level prediction distribution for the 28 class-A materials at the same time point. Both are complementary representations of the same prediction result at different levels.

In general, the CNN-LSTM model can provide the quantity prediction results for future time points for the inventory management of in vitro diagnostic reagent production materials, and provide data support for enterprises to carry out classification control, inventory early warning and procurement arrangement. In this way, the relationship between category recognition, quantity prediction and system application is clearer, and the result interpretation is more in line with the actual use logic in the inventory management scenario.

Table 3: The inventory predictive value of four kinds of medical instruments

Medical instruments type	Predictive value
A	1331
B	879
C	747
CVA	736

As shown in Table 3, the forecast results show the inventory distribution of four types of materials A, B, C and CVA in December 2024 from the category level, which can be used for the total inventory control at the enterprise level. To further illustrate the internal structure of high-value class A materials, FIG. 5 shows the subdivision results of 28 SKUs of class A at the same prediction time point. The complementary display of the two belonging to the same prediction node: Table 3 reflects the total amount of categories, and Figure 5 reflects the SKU details of category A. After verification, the sum of the predicted values of 28 SKUs in Figure 5 is consistent with the total predicted value 1331 of type A in Table 3, which can jointly support the inventory decision from total to fine items.

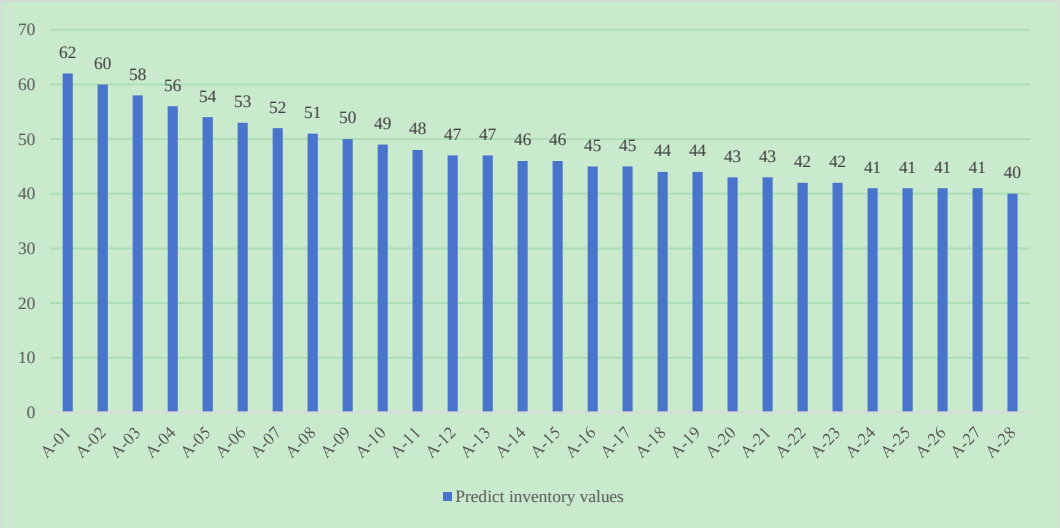

Figure 5: Bar chart of each SKU forecast inventory for category A material in December 2024

4 Conclusion

This study focuses on the inventory management of production materials in medical device enterprises. This paper studies the inventory identification and prediction of medical products, and constructs an intelligent identification and optimization model for medical product inventory based on deep learning. The ABC-CVA combined classification method is used to classify the raw materials of in vitro diagnostic reagents, and a medical product inventory prediction model based on CNN-LSTM is proposed. The main findings of this study are as follows:

(1) The inventory of medical device production materials in the sample enterprise is divided into four categories: A, B, C and CVA, accounting for 14.00%, 22.50%, 58.00% and 5.50%, respectively. Accordingly, differentiated inventory management priorities and control strategies can be formed.

(2) The CNN-LSTM model is superior to the baseline models in inventory prediction and identification. For Class B material inventory with task length more than 1 month, the MAE, RMSE and SMAPE of the model are reduced by at least 2.12%, 2.75% and 1.88%, respectively. For Class C material inventory, the MAE, RMSE and SMAPE are reduced by at least 4.15%, 7.38% and 3.65%, respectively. As the time series becomes longer, the prediction accuracy of the proposed model for medical device inventory identification decreases, but it remains better than the baseline models.

(3) The CNN-LSTM model provides quantitative predictions for the inventory status of the four material categories in the sample company for December 2024. Therefore, the enterprise can obtain the inventory of all material SKUs according to the prediction results, so as to improve medical device inventory management and realize reasonable inventory identification.

In the research of intelligent medical supply chains, the significant advantages of deep learning in data analysis and pattern recognition have been gradually recognized. The CNN-LSTM model proposed in this paper has achieved good results in the accurate prediction of medical product inventory. In the future, we can try to integrate more kinds of deep learning or machine learning models. By combining different types of models, more powerful hybrid models can be developed to further improve the accuracy of inventory prediction.

5 Future Work

In addition, the CNN-LSTM intelligent identification and optimization model for medical device inventory developed in this study realizes deep data integration and system interoperability with the Manufacturing Execution System (MES), Warehouse Management System (WMS) and Warehouse Control system (WCS) of intelligent manufacturing enterprises in the field of medical products. By establishing an enterprise-level data intermediate platform, multi-source heterogeneous data such as MES production plan, real-time work order information, WMS inventory status, in-out warehouse dynamics, wcs equipment operation log, task commands and so on are aggregated to form a unified medical product inventory management data asset pool. Using the cleaning, integration, and time series data services provided by the platform in, the CNN-LSTM model achieves more efficient feature extraction and dynamic inventory prediction, thus supporting advanced applications such as real-time inventory visualization, demand fluctuation warning, and intelligent replenishment decisions. In the future, promoting bidirectional data flow between MES/WMS/WCS systems and AI model platforms will help build an integrated closed loop

of "perception, prediction and decision execution". This will not only enhance the responsiveness and management precision of the healthcare supply chain, but will also lay the technical foundation for smart healthcare scenarios such as digital twins, flexible manufacturing, and adaptive supply chains.

From an application perspective, the value of the proposed model is not limited to statistical prediction accuracy. In the actual inventory management environment, the output forecast can be linked with production planning, purchase scheduling and inventory early warning rules to form a more operational decision-making process. Category-level predictions, for instance, serve to flag material groups approaching predefined warning thresholds, whereas SKU-level decomposition supports more granular replenishment decisions for high-priority items. The model thus functions as a bridge from historical data analysis to routine inventory operations. Extensions of this work may integrate the model with enterprise information systems—such as MES, WMS, and WCS—to establish a unified data pipeline encompassing production orders, warehouse transactions, and equipment execution logs. Following system integration, the forecasting module would receive more timely input signals, enabling earlier responses to shifts in production demand and inventory drawdown. Visualization components could further display forecasted inventory fluctuations, highlight anomalous trends, and generate category-specific replenishment guidance. Such enhancements would strengthen both the interpretability and practical utility of the model in real-world industrial environments. Therefore, the future research direction should not only refine the prediction algorithm itself, but also strengthen the linkage between the intelligent prediction results and the enterprise inventory decision-making workflow with higher operational consistency and timeliness, so that the model can support the closed-loop process of perception, prediction, early warning and execution in the smart healthcare supply chain.

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