

# Blockchain-Enabled Digital Transformation in Pharmaceutical Cold Chain Management Using Hybrid Deep Neural Networks

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## ABSTRACT

The pharmaceutical cold chain is a specialized unit in the logistics field that has demanding needs for transportation and warehousing in the supply chain to protect the reliability of pharmaceutical goods and guarantee the health security of individuals. The cost of the pharmaceutical cold chain is high. Recently, pharmaceutical drug traceability systems have been established as essential devices to develop the digital visibility and transparency of the supply chain. The complete pharmaceutical cold chain consists of a chain of links, such as storage and use, production, and transportation. Blockchain (BC)-based drug traceability offers an encouraging method for a distributed shared data platform that is reliable, permanent, and trustworthy. This paper proposes a Digital Transformation in Pharmaceutical Cold Chain Management using a Hybrid Deep Neural Network (DTPCCM-HDNN) model, intending to enhance digital transformation and transparency in pharmaceutical cold chain management by utilizing BC and advanced models. Initially, the data preprocessing stage employs the RobustScaler method to clean, transform, and structure raw data into an appropriate format. The feature selection process involves the Mutual Information (MI), Recursive Feature Elimination (RFE), and Random Forest Importance (RFI) methods to choose crucial features from the dataset. Finally, a hybrid Convolutional Neural Network and Long Short-Term Memory (CNN-LSTM) technique is implemented for prediction. The performance of the DTPCCM-HDNN approach was examined on a pharmaceutical SC optimization dataset. The DTPCCM-HDNN approach demonstrated great performance, achieving an MSE of 0.0673, an RMSE of 0.2595, and an MAE of 0.2245.

*Keywords-pharmaceutical cold chain management; hybrid deep neural networks; digital transformation; blockchain; RobustScaler; recursive feature elimination; random forest importance; convolutional neural network; long short-term memory*

## I. INTRODUCTION

The pharmaceutical cold chain is a specialized part of the logistics sector from the producer to the user of refrigerated medicines [1]. The complete pharmaceutical cold chain comprises a collection of links, namely production, transportation, storage, and utilization. The pharmaceutical cold chain involves diagnostic biological products, therapeutic biological products, and preventive biological products [2]. Representative biological products comprise several antisera, vaccines, toxoids, antitoxins, diagnostic reagents, immune preparations, etc. Pharmaceutical cold chain management is facing unmatched opportunities and difficulties [3]. With the growth of medicine and biotechnology, the market for refrigerated pharmaceutical products is growing, and the scale of the pharmaceutical cold chain is expanding [4]. The cold chain requires suitable temperature environments. It is essential to understand temperature control by utilizing special storage, loading, and unloading facilities and cold storage units [5].

Currently, the field of pharmaceutical cold chain is still in an initial phase of expansion. The present reach and implementation of pharmaceutical cold chain systems are inadequate [6]. BC has developed as a ground-breaking technique, providing a system that is transparent and irreversible without the need for authorized representatives. It is a collection of timestamped, tamper-proof sequences of blocks linked with cryptographic locks. Every new block placed at the end of the chain comprises a unique code or a reference to the data that was added to an earlier block. BC technologies improve product safety and ensure accurate tracking in pharmaceutical supply chains. BC presents a tamper-proof decentralized platform that enhances reliability, transparency, and accountability among stakeholders, helping to combat counterfeit drugs. Integration of BC with Deep Learning (DL) can protect data, provide competitive advantages, and monitor conditions such as temperature throughout the supply chain to prevent resource losses [7-10].

In [11], a BC Non-Fungible Token-driven Drug Traceability for Enhanced Pharmaceutical Supply Chain Management (BNFTDT-EPSCM) technique was introduced. In addition, this technique utilizes an improved Byzantine fault-tolerant consensus (RB-BFT) trust model. In [12], a secure method was proposed by integrating ML with BC, using an Improved Honey Badger Algorithm (IHBA) with EBC features to improve LSTM performance. In [13], a safe and effective BC-driven traceable supply chain structure was presented. In [14], several IoT solutions for the pharmaceutical cold chain were examined. In [15], a novel cold chain method was proposed based on the Reference Architecture (RA) and an improved Reference Process Model (RPM). This approach also used the Delphi method to present a methodical decision context. In [16], an innovative technique integrated IoT with BC in the health sector. In [17], a smart secure network framework was introduced, using the Bee-Ant Optimizer Algorithm (BAOA) for tuning. In [18], a secure BC-IoT model integrated a Modified Capsule Neural Network (M-CapNN) for prediction and detection, and a hybrid cryptographic system with the Equilibrium-Enriched Siberian (EES) approach to improve data security and key management. In [19], a Supply Chain Network based on BC Technology (SCN-BT) integrated a hybrid LSTM network with Gray Wolf Optimization (GWO) to improve forecasting. In [20], a BC-Enabled Trust Management Framework used Federated Learning (FL) to enhance security, transparency, and efficiency. In [21], a BC-based framework was integrated with DL for anomaly detection. Most studies incorporated BC with IoT, ML, and DL to improve supply chain security, but lacked unified solutions for scalability, real-time processing, and adaptive optimization. The research gap lies in creating frameworks that integrate robust consensus with advanced prediction to improve the resilience of the supply chain.

This study proposes a Digital Transformation in Pharmaceutical Cold Chain Management Using Hybrid Deep Neural Networks (DTPCCM-HDNN) model, examining its performance on a pharmaceutical supply chain optimization dataset. This study:

- Uses the RobustScaler method to effectively clean, transform, and normalize raw data, ensuring enhanced data quality and consistency, and improving the reliability and performance of subsequent analysis and modelling steps.
- Integrates Mutual Information (MI), Recursive Feature Elimination (RFE), and Random Forest Importance (RFI) techniques to efficiently detect and choose the most relevant features, improve model accuracy, and mitigate dimensionality for more efficient prediction.
- Implements a hybrid CNN-LSTM architecture for capturing both spatial and temporal patterns in time series data, improving forecast accuracy and robustness in complex environments.

The novelty of this study is the incorporation of various feature selection techniques, such as MI, RFE, and RFI, with a hybrid CNN-LSTM model, providing a comprehensive and effective approach to time series prediction. This integrated method improves accuracy and robustness.

## II. MATERIALS AND METHODS

The primary intention of this study is to enhance digital transformation and transparency in pharmaceutical cold chain management by leveraging BC and advanced models. The DTPCCM-HDNN model involves data preprocessing, feature selection, and a hybrid prediction model. Figure 1 describes the complete process of the DTPCCM-HDNN technique.

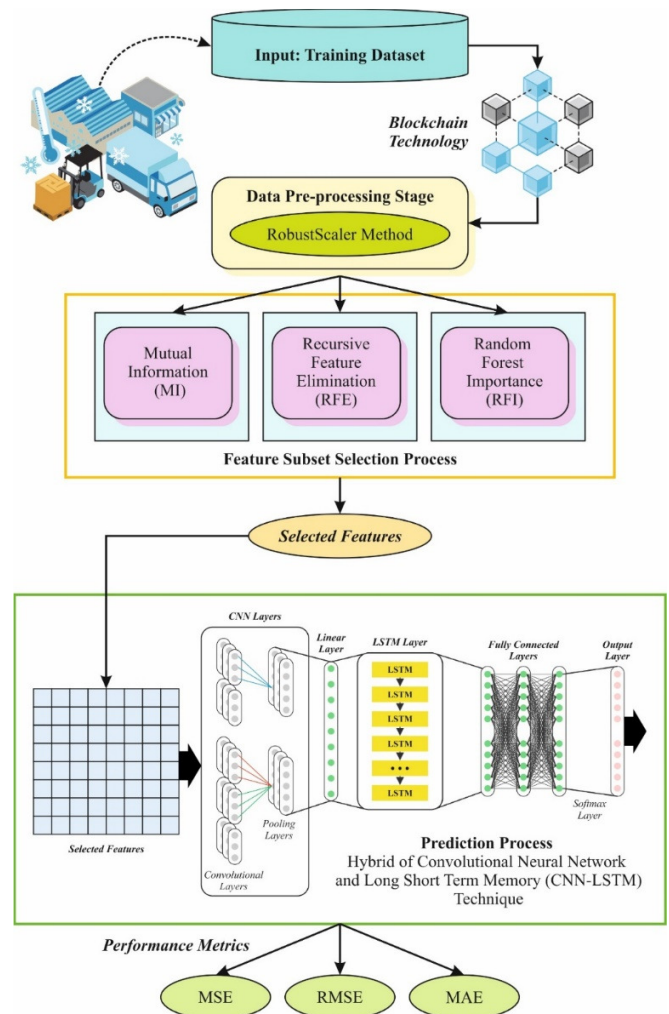


Fig. 1. Overall procedure of the DTPCCM-HDNN technique.

### A. RobustScaler-Based Preprocessing

Initially, the data preprocessing stage employs the RobustScaler method to clean, transform, and structure raw data into an appropriate format [22]. This model was chosen for its efficiency in mitigating the impact of outliers, unlike standard scaling models that are sensitive to extreme values. This results in more stable and reliable model performance, specifically with datasets comprising significant noise or anomalies. RobustScaler is a data normalization model intended for decreasing the effect of outliers. Unlike StandardScaler, which alters data depending on the standard deviation and mean, it employs the Interquartile Range (IQR)

and median, making it stronger against skewed distributions and greater values. This transformation is described by:

$$x_{scaled} = \frac{x - Q_2}{Q_3 - Q_1} \quad (1)$$

where  $x$  represents the original data value being scaled using the IQR for normalization.  $Q_1$  and  $Q_3$  refer to the first and third quartiles, respectively, and  $Q_2$  signifies the median.

In datasets, outliers frequently occur due to recording errors, medical variations, or rare conditions. Outliers can negatively impact model performance, especially in scale-sensitive models. RobustScaler is effective for enhancing stability by scaling features based on their IQR, reducing the influence of extreme values. It is used during preprocessing to mitigate outlier effects, but not for outlier detection or extraction.

### B. Feature Subset Selection Method

Feature selection is performed using the MI, RFE, and RFI methods to select the most crucial features from the dataset [23]. This hybrid approach is chosen for its complementary merits in capturing both linear and nonlinear dependencies. RFE iteratively removes less significant features based on model performance, and RFI evaluates feature importance through ensemble learning. This hybrid approach ensures a robust and comprehensive selection of relevant features, enhancing model accuracy and mitigating overfitting compared to single-method techniques. Using three experimentally selected feature selection techniques, such as RFE, RFI, and MI, provides a different method to detect the most relevant features. These techniques are chosen to depict the three main classes of feature selection techniques, namely wrapper-, embedded, and filter-based techniques.

#### 1) Mutual Information (MI)

MI measures the dependency between two random variables, capturing both linear and nonlinear relationships. As a filter-based feature selection method, MI computes the significance of each feature by evaluating its statistical relevance to the target variable. This ability is specifically helpful for detecting complex patterns in volatile data, such as cryptocurrency markets. Then, the MI amid dual random variables  $x$  and  $y$  is described by:

$$I(x, y) = \sum_{i=1}^n \sum_{j=1}^n p(x(i), y(j)) \log \left( \frac{p(x(i), y(j))}{p(x(i)) \cdot p(y(j))} \right) \quad (2)$$

$I(x, y)$  quantifies the amount of data shared between these variables by summing over all possible values  $i$  and  $j$ . The term  $p(x(i), y(j))$  is the joint probability distribution of  $x$  and  $y$ , while  $p(x(i))$  and  $p(y(j))$  are their respective marginal probabilities. The logarithmic ratio measures how much knowing one variable mitigates uncertainty about the other, making mutual data a key metric for evaluating dependency or shared data between variables. Finally,  $MI$  is 0 while  $x$  and  $y$  refer to statistically independent variables specified by:

$$p(x(i), y(j)) = p(x(i)) \cdot p(y(j)) \quad (3)$$

#### 2) Recursive Feature Elimination (RFE)

RFE is a wrapper-based model. Wrapper techniques consist of training a method iteratively and assessing a subset of features based on model performance. RFE recursively extracts the lower significant features depending on the performance of the process, offering a systematic manner of detecting the related features. This method is specifically efficient to ensure that only the most effective indicators are retained, thereby reducing noise in the model prediction.

#### 3) Random Forest Importance (RFI)

RFI refers to the embedded class of feature selection approaches. This embedded approach accomplishes feature selection during the model training process, ranking features based on their contribution to decreasing the model error in an ensemble structure, providing insight into the significance of features as they interrelate in the method.

### C. Hybrid CNN-LSTM Prediction

DTPCCM-HDNN employs a hybrid of CNN and LSTM techniques for the prediction model [24]. The hybrid model integrates the merits of CNN in automatic feature extraction with LSTM's ability to capture long-term dependencies in sequential data. This synergy improves prediction accuracy and robustness for time series forecasting compared to standalone CNN or LSTM models. It effectively handles intrinsic data patterns, making it ideal for dynamic and volatile environments.

CNN is a DL approach designed to process spatially structured data, and its structure comprises an activation function, a pooling layer, and a convolutional layer. The convolutional layer performs local weighted averaging to reduce correlations and cut parameters through sharing. The activation function adds non-linearity, improving the model's ability to capture intrinsic patterns. The pooling layer downsamples while retaining key features, further enhancing the model's expressiveness. This model may successfully seize the nonlinear spatio-temporal dependency among numerous features, therefore increasing the accuracy. Every convolutional layer is characterized by:

$$h_{ij}^k = f((w^k * x)_{ij} + b_k) \quad (4)$$

where  $x$  and  $h_{ij}^k$  refer to the convolutional layer's input and output vectors, using the location of the  $j^{\text{th}}$  column and the  $i^{\text{th}}$  row,  $f$  denotes an activation function like ReLU, Leaky, Sigmoid, etc.,  $w^k$  signifies a convolutional kernel's weighted matrix linked to the  $k^{\text{th}}$  feature maps,  $b_k$  denotes a bias vector, and  $*$  represents the convolution process. The pooling layer reduces feature dimensions, decreasing computation and parameters while minimizing overfitting. Max-pooling is used to effectively capture dominant multisource features.

LSTM overcomes vanishing and exploding gradient problems in long sequences by using a cell state and three gates: input, output, and forget. The forget gate is crucial for selectively discarding or retaining past data, freeing memory for new essential data, and preventing performance degradation caused by data overload, as shown in:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (5)$$

where  $f_t$  refers to the gate that controls the forgetting of older memories,  $w_f$  denotes the forget gate's weighted matrix,  $h_{t-1}$  signifies hidden states of the preceding instant,  $x_t$  symbolizes the input of the current time step,  $b_f$  represents the bias term of the forget gate, and  $\sigma$  denotes the Sigmoid activation function.

The input gate controls the integration of new data by filtering and combining essential features into the cell state, dynamically assessing the relevance of current inputs. The input gate includes two main computing processes:

1. The input gate weights are computed to define which data in the present input contributes to longer-term memory.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (6)$$

where  $i_t$  refers to the input gate weight that controls the learning of candidate memory,  $W_i$  refers to the input gate's weighted matrix, and  $b_i$  signifies the biased term of the input gate.

2. A candidate memory for the present input is created to control novel attributes that require being learned as:

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \quad (7)$$

where  $\tilde{C}_t$  denotes the candidate memory,  $W_C$  symbolizes a weighted matrix of the candidate memory,  $b_C$  denotes the bias term for the candidate memory, and  $\tanh$  signifies the hyperbolic tangent activation function.

Utilizing the results of the input gate weighted computation and the produced candidate memory, a combination of historic and novel knowledge is implemented to upgrade the longer-term cell state memory as:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \quad (8)$$

The output gate is an essential process in LSTM to control the outside perceptibility of memory data, and its part is to select what must be distributed or output to the following layer at the current moment, as:

$$\begin{aligned} o_t &= \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \\ h_t &= o_t \cdot \tanh(C_t) \end{aligned} \quad (9)$$

where  $o_t$  denotes the output gate weight that controls the cell state  $C_t$ ,  $h_t$  denotes the current hidden state that is distributed to the following instant as shorter-term memory or applied for prediction,  $W_o$  and  $b_o$  denote the output gate's weighted matrix and biased term,  $\sigma$  represents the Sigmoid activation function, and  $\tanh$  denotes the hyperbolic tangent activation function.

### III. PERFORMANCE ASSESSMENT

The performance of the proposed DTPCCM-HDNN model was evaluated using a pharmaceutical supply chain optimization dataset [24]. This dataset was developed mainly to support research in drug inventory management and supply chain performance. It includes real-time inventory data along with demand prediction data, allowing investigation of stock availability, demand pattern, and distribution planning in the pharmaceutical sector. It is appropriate to develop prediction

approaches to estimate demands, optimize inventory levels, and enhance logistics decisions. With the combination of inventory tracking and demand prediction, it can be used with artificial intelligence approaches to address challenges in pharmaceutical supply chain management.

The proposed method was developed using Python 3.6.5 on an i5-8600K CPU, 4GB GPU, 16GB RAM, 250GB SSD, and 1TB HDD, using a learning rate of 0.01, ReLU, 50 epochs, 0.5 dropout, and a batch size of 5. Figure 2 shows the convergence curve of the DTPCCM-HDNN model. The results signify that the DTPCCM-HDNN approach converges by gaining a value of 0.95312 over various iterations on the implemented data.

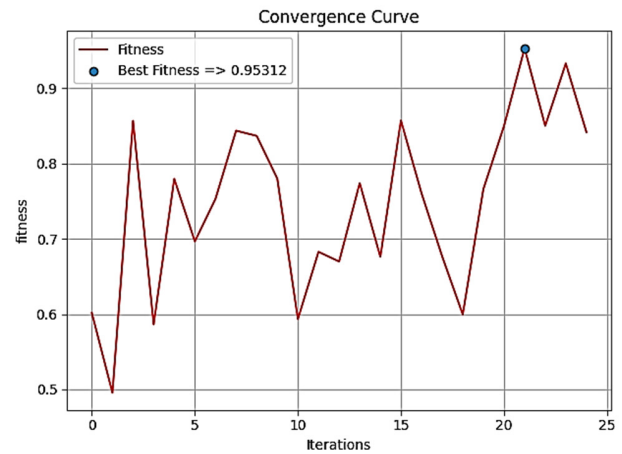


Fig. 2. Convergence curve of the proposed DTPCCM-HDNN model under various iterations.

Table I shows the training and testing set results. In the training set, the DTPCCM-HDNN technique achieved MSE, RMSE, and MAE of 0.0676, 0.2599, and 0.2252, respectively. In the test set, the DTPCCM-HDNN model achieved MSE, RMSE, and MAE of 0.0673, 0.2595, and 0.2245, respectively.

TABLE I. TRAINING AND TEST RESULTS OF THE PROPOSED DTPCCM-HDNN METHOD

Metrics	Training set	Testing set
MSE	0.0676	0.0673
RMSE	0.2599	0.2595
MAE	0.2252	0.2245

### IV. CONCLUSION

This study presented the DTPCCM-HDNN approach to enhance digital transformation and transparency in pharmaceutical cold chain management by utilizing BC and advanced models. Initially, the data preprocessing stage employed the RobustScaler method to clean, transform, and structure raw data into an appropriate format. In addition, feature selection was performed using MI, RFE, and RFI. Finally, a hybrid CNN-LSTM technique was implemented for prediction. The performance of the DTPCCM-HDNN approach was examined on the pharmaceutical supply chain optimization dataset. The DTPCCM-HDNN approach demonstrated superior performance with an MSE of 0.0673, an RMSE of 0.2595, and

an MAE of 0.2245, outperforming other models. The limitations of the DTPCCM-HDNN approach comprise restricted evaluation on a single dataset, which may affect generalizability across diverse conditions. In addition, the proposed model lacks real-time deployment validation and interpretability analysis. Expanding the model to cross-market scenarios and incorporating explainable AI could enhance practical applicability and trust.

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