

Original Article

An Integrated Blockchain with a Hybrid Deep Learning Framework for Enhanced Resource Efficiency in the Supply Chain Healthcare Industry

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Received: 19 September 2025

Revised: 20 October 2025

Accepted: 18 November 2025

Published: 29 November 2025

Abstract - Over the years, fast development has occurred in the healthcare industry, and major challenges healthcare experts and stakeholders face are supply chain management. With an excessive growth in the need for healthcare services and the requirement for effective, cost-effective, and higher-quality healthcare delivery, Healthcare Supply Chain Management (HSCM) became a key aspect in considering success in healthcare systems. In recent times, Blockchain (BC), Artificial Intelligence (AI), and the Internet of Things (IoT) have shown certain possibilities to revolutionize HSCM. The HSCM consists of expiration, counterfeits, product recalls, and monitoring of product supply shortages. BC, incorporated with IoT, is a new technology that can provide a practical solution to the SCM in healthcare. In this manuscript, a Blockchain-Integrated Hybrid Deep Learning model for Supply Chain Management and Resource Efficiency (BCHDL-SCMRE) model is presented in the Healthcare Industry. The paper aims to develop an intelligent and secure framework using advanced techniques to improve transparency, efficiency, and trust in SCM within the healthcare industry. Initially, the BC technology is applied in healthcare supply chains to ensure transparency and security. Next, the Z-score normalization is used in the data pre-processing phase to normalize the input data. To select optimal features, the feature selection process is executed by the Modified Rain Optimization (MRO) algorithm. Furthermore, the hybrid of a Temporal Convolutional Network and Gated Recurrent Unit (TCN-GRU) technique has been deployed for classification purposes. At last, the improved Sparrow Search Algorithm (SSA) is applied for parameter tuning to guarantee that the optimal hyperparameters are picked for improved precision. To display the heightened performance of the proposed BCHDL-SCMRE system, a complete performance assessment is conducted. The comparative outcomes informed the improvised features of the BCHDL-SCMRE method.

Keywords - Blockchain, Supply Chain Management, Healthcare Industry, Internet of Things, Resource Efficiency, Improved Sparrow Search Algorithm.

1. Introduction

In numerous sectors, the successful management and distribution of goods and services is crucial. The term logistics is often used to describe this process [1]. The HSCM observes and manages the flow of healthcare products and services from the manufacturing plant to end-users [2]. It is a crucial factor in the healthcare sector that encompasses the preparation, procurement, storage, and distribution of medical supplies, equipment, and drugs [3]. An efficient healthcare supply chain system can provide medicines and flexible treatment schedules tailored to their availability and preferences [4]. From the start, the HSCM entails getting the best suppliers with better deals for healthcare-related products, handling stock at all levels of the delivery process, including the tracking of expiration dates, ensuring efficient movement of products and their efficient delivery, and

guaranteeing the quality of the products following the industrial regulations, although upholding cost control and supplier relationships [5]. The healthcare industry has yet to undergo digital transformation and has not undergone changes in a similar manner to other sectors. To offer patients improved treatment, the healthcare industry needs to adapt technologically [6]. Integrating techniques such as Blockchain (BC) can demonstrate its importance in the healthcare sector. By addressing the current problems in healthcare, BC can entirely change the industry [7]. It stores and exchanges sensitive healthcare data in a private, secure, and reliable way, utilizing cryptographic models and decentralized consensus mechanisms [8]. Besides flawless data exchange, it can assist in connecting multiple healthcare systems and provide real-time access to patients' historical data, thereby eliminating unnecessary checks. Patients can effectively manage their



healthcare data using BC while maintaining data protection and obtaining explicit consent [9]. BC applications in healthcare are classified into patient data management, SCM, drug traceability, claims adjudication, clinical trials, data security, billing, etc.

Of these, the SCM is regarded as one of the most effective.

Furthermore, an effectual SCM allows patients to get appropriate, high-quality treatment while minimizing expenses and waste [1].

Nevertheless, HSCM encounters numerous difficulties that impede its effectiveness and efficacy. Developing techniques such as IoT, AI, and BC can transform HSCM by addressing some of the key issues. An instance of employing AI is the development of demand forecasting [10]. Simultaneously, IoT is a pillar of strength for tracking deliveries, and BC provides a clear forum for all parties with a vested interest to participate in operations. By using these techniques, HSCM turned out to be more effective, cost-efficient, and patient-centric [11].

2. Related Works

Ma and Kang [12] examined the fundamental processes by which digital intelligence enhances strategic decision optimization in HSCM. Employing the Resource-Based View (RBV) and Dynamic Capabilities Theory (DCT) as a basis, a multi-stage, indirect pathway is established, wherein digital intelligence initially enhances a firm's innovation capacity, subsequently fostering improved supply chain resilience, which ultimately culminates in superior decision-making and continuous improvement in decision-making performance. Karbassi Yazdi et al. [13] explored the role of BC technologies in facilitating decarbonization in HSCM within the framework of Industry 4.0. A new hybrid proposed methodology integrating the Z-number Logarithm Methodology of Additive Weights (ZLMAW) and Fuzzy Spherical Analytical Hierarchy Process (FS-AHP) is created to tackle the intricacies and vagueness built into this field.

This study identifies crucial factors influencing the implementation of BC in decarbonized SCM and ranks healthcare facilities based on their potential for successful implementation. Ahmed et al. [14] delved into the BC application for enhancing pharmaceutical supply chains by allowing the tracking of medicines from production to end-user delivery. Moreover, the incorporation of BC with IoT systems gives practical monitoring of storage conditions and enables product integrity. This research examines the methodological framework, implementation issues, and the BC's ability to transform healthcare logistics, enhance patient safety, and improve operational efficacy in pharmaceutical supply chains.

Dar et al. [15] presented an approach for more open and clear supply chain operations through the use of BC and AI techniques. It employs a qualitative method to investigate how BC and AI can lead to clearer supply chains from an environmental and social perspective. Given the incorporation of BC and AI from many viewpoints, triangulation will be attained to promote traceability and transparency. Dash et al. [16] offered a methodical approach to constructing a blockchain-based Supply Chain Risk Management (SCRM) PoC. This PoC develops a supply chain technique to assess feasibility and quantify key performance factors. This investigation thoroughly assesses the efficiency of the SCRM BC among several test scenarios, presenting different numbers of clients and organizations. Nanda et al. [17] introduced an innovative technique for Integrated IoT with BC in HSCM. With this technique, it can remove all supply chain-related challenges between suppliers and consumers. This investigation aims to integrate the BC system with IoT to design smart HSCM systems. Farooqui and Parikh [18] suggested a method that facilitates the industrial sector's access to agricultural data while also providing farmers with crop-related information. This approach is effective for managing the supply chain to ensure reliable delivery. IoT systems are vulnerable to attacks due to storage constraints, limited computing capabilities, and other factors. Blockchain, in conjunction with the Internet of Things, provides a resolution to the challenges faced by numerous industries. Blockchain and smart contracts are technologies that have garnered significant interest.

3. Proposed Methodology

This paper develops a BCHDL-SCMRE model in the Healthcare Industry. The paper aims to develop a secure and intelligent structure using advanced techniques to improve trust, transparency, and efficiency in SCM in the healthcare sector. It contains BC technology, data scaling, feature selection, classification, and parameter tuning models. Figure 1 represents the block diagram of the BCHDL-SCMRE model.

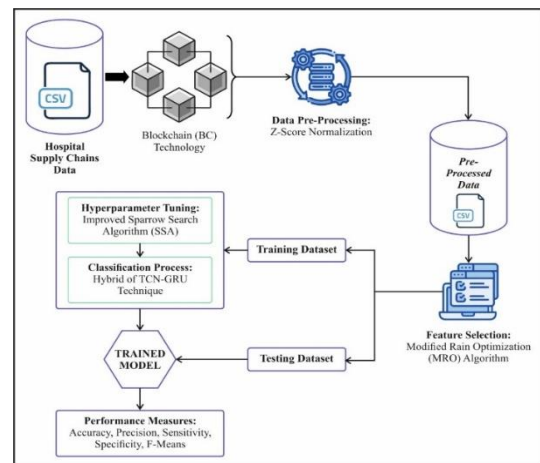


Fig. 1 Block diagram of BCHDL-SCMRE model

3.1. BC Technology using Healthcare Supply Chains

To begin with, the BC technology is used in HSCM to guarantee security and transparency. The present Group Purchasing Organizations (GPO) contract management comprises various data systems and a lack of transparency and automation among their providers and suppliers [19]. The GPO needs to determine a model that promotes successful co-operation amongst Healthcare Supply Chains (HCSC) stakeholders, together with permitting manufacturers to interact and convey data with distributors by reducing timeline and lowering price differences to offer pricing upgrades and modifications that arise in the GPO, because of its key features, like a distributed and decentralized network, data immutability, and a consensus mechanism. The transaction is added in blocks, while every block contains a valid transaction. The blocks are chained to each other by miners to generate BC.

Furthermore, they accept the consistency protocol to select the miner. In recent times, BC has been a subject of interest in several productions, including HCSC. It can improve the procedure that is performed multiple times by the GPO:

- Healthcare contracts are a complex, multi-phase process; here, some of this focus is on pricing negotiation. Whereas pricing valuation is vital, stakeholders consider modifications that arise to avoid errors and wasted time on rework among providers and suppliers. BC is capable of triggering events once a modification occurs, thus notifying each stakeholder in the network.
- Existing solutions cannot offer a holistic method that comprises every stakeholder in the HCSC.
- A considerable volume of time and effort is presently spent on pricing errors, exchanging rebates, and GPO administrative fee payments since the agreement is modified frequently, making the procedure extremely ineffective. Thus, BC is capable of tackling this problem due to some alteration that takes place in the life of an agreement that is timestamped and recorded. Thus, they are capable of knowing precisely after the modification happens.
- GPOs frequently discover it is tedious to continuously monitor providers and verify whether they fulfill and adhere to the promised volume specified on the contract. BC enables GPO to effortlessly alert and track providers with the assistance of a smart contract. Figure 2 indicates the structure of blockchain.

3.2. Input Data Scaling using Z-score Model

Then, the Z-score normalization is used in the data preprocessing step for normalizing the input data. This normalization contains a standard deviation of 1 and a mean of 0 [20]. It is beneficial to ensure that all the data is gathered from users. It has a similar scale without bias resulting from the unusually huge values. It permits the features originated

by social interaction to be relevant and effectively employed in models. The Z-score standardization is calculated by employing Eq. (1) for each point of data. x_i in the dataset:

$$z_i = \frac{x_i - \mu}{\sigma} \quad (1)$$

The data point x_i signifies the initial data point, and Z_i Denotes the standardized value of a data point. Its average or mean is represented by μ . The standard deviation of the dataset is depicted as σ .

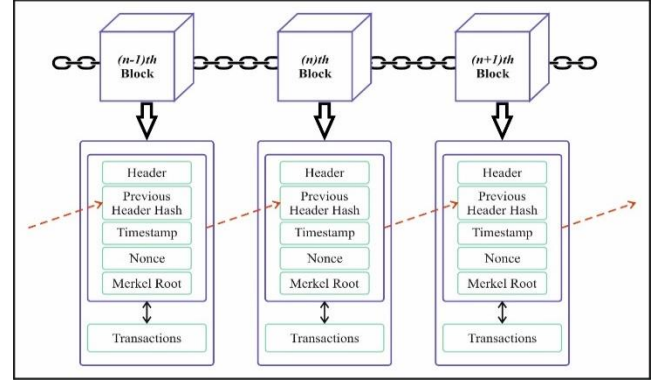


Fig. 2 Structure of blockchain

3.3. MRO-Based Feature Selection Method

To select the optimal features, the FS process is implemented by the MRO algorithm. This optimization is inspired by falling rain from a higher to a lower spot [21]. It is employed to decrease the feature dimensionality. The ROA is initialized with the population of features. This MRO model is initialized with the extracted set of features.

$$\tilde{M}_s = \{\bar{f}_{n,1}, \bar{f}_{n,2}, \bar{f}_{n,3}, \dots, \bar{f}_{n,k}\} \quad (2)$$

$$n \in \{1, 2, 3, \dots, \hat{f}\} \quad (3)$$

Now, \tilde{M}_s indicates the feature set. The optimal set of features is selected to employ the MRO method, which reduces the size of the features.

$$\hat{f}_n = \bar{D}_{uniform}[\bar{U}_n, \bar{L}_n] \quad (4)$$

Where, \bar{U}_n indicates the upper bound data, $\bar{D}_{uniform}$ denotes the uniform distribution, and \bar{U}_n represents the \bar{L}_n Lower bound data. Then, the data position is upgraded randomly through the succeeding Eq. (5).

$$\bar{P}_f = \bar{P}_{arbitrary}(\bar{I}_{initial} * \bar{I}_{max}) \quad (5)$$

Now, $(*)$ function indicates the unit vector dimension, \bar{P}_f Denotes the optimum place of features, $\bar{I}_{initial}$ represents the initial iteration, \bar{I}_{max} depicts the maximal iteration and

$\bar{P}_{arbitrary}$ Indicates the arbitrary position. Furthermore, the optimum position based on the Nearest Point (\bar{Np}).

$$\bar{O}_F(\bar{Np}_{pk}^m) < \bar{O}_F(\bar{f}_{pk}^m), \quad m = 1, 2, 3, \dots, M_p \quad (6)$$

Now, \bar{O}_F Denotes the optimum set of features based on the control of important features from low to high.

$$\hat{F}_{rak} = \bar{O}_F |\bar{I}_{max} - \bar{O}_F| \quad (7)$$

While, \bar{O}_F denotes the optimum set of features, F_{rnak} represents the ranked features and \bar{I}_{max} Depicts the maximal iteration counts. The optimum chosen feature is the ranking feature to obtain the value of the threshold (T_h), and it is depicted as $\hat{F}_{rak} > \bar{th}$. It reduces the dimension of the feature set by extracting unimportant features. The radius of the droplet progressively decreases if it is terminated at least one position, enhancing the precision.

$$\text{fitness} = \min(CF) \quad (8)$$

Now, CF refers to the cost function. The MRO modifies the ROA, like the arbitrary FS in ROA tends to skew the entire precision. Concurrently, approximating the original and matching opposing solutions.

$$Z'_i = UB + LB - Z_i, \quad Z_i \in [UB, LB] \quad (9)$$

The upper and lower limits equivalent to the searching region are depicted UB , and LB , respectively. It improves searching space exploitation and exploration, which increases the ROA for feature selection. By adding solutions to the existing population, the learning models aid the method to evade local optima and explore diverse places.

3.4. Classification using TCN-GRU Method

Besides, the hybrid of the TCN-GRU technique has been applied for the classification process. TCN is a DL framework specially tailored for handling sequential data. Separated from the traditional Convolutional Neural Network (CNN) [22]. TCN attains enhanced representation of longer-range dependences and allows extremely effective parallel processing by combining dilated and causal convolutions into the temporally-aware structure. Now, TCN has developed as an extensively accepted predictive method across different engineering fields. Causal convolution enforces temporal causality in predictions by restricting the convolutional kernel to utilize only current and historical input, effectively mitigating the risk of future information leakage. The receptive field in sparse sampling during convolutional procedures improves with increasing dilation rates. Once TCN is built with a larger layer count, residual link must be used among dissimilar layers for addressing the exploding or

vanishing gradient issues in deep networks, thus enhancing convergence rates and training stability. GRU is an advanced Recurrent Neural Network (RNN) that solves the vanishing gradient problem in its typical applications. GRU simplifies the gating architecture by reducing parameters while preserving performance compared to LSTM. It is now the most common RNN in applied technologies. The comprehensive updated formulations for the GRU parameters are shown in Eq. (10):

$$\begin{cases} r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r) \\ z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z) \\ h_t^* = \tanh(W_h x_t + U_h (r_t \odot h_{t-1}) + b_h) \\ h_t = (1 - z_t) \odot h_t^* + z_t \odot h_{t-1} \end{cases} \quad (10)$$

Whereas x_t denote input at time t ; W and U means weighted matrices; b denote bias; \tanh refers to activation function of hyperbolic tangent; z_t and r_t characterize the update gate and reset gate correspondingly; h_t^* indicate the candidate's Hidden Layer (HL) while h_t Stands for the last HL.

GRU may process input from the current input sequence and the prior time step's hidden layer. The reset gate controls the preceding hidden layer used to compute the current time step candidate hidden layer. The gate of update defines whether the HL preserves older data from the preceding time step. Once the gate of reset approaches 0, the method successfully ignores historic data to concentrate on new modes, but maximum reset values maintain context stability. Similarly, the gate of update values closer to 1 prioritizes memorization of longer-term dependences, while low values highlight direct extraction of the features. The gating mechanism offers paths to shape the balance between previous and current information in the last output, making GRU mainly beneficial to model temporal patterns in time series tasks.

3.5. SSA-based Parameter Tuning Model

Eventually, the SSA is applied for parameter tuning to ensure that the optimal parameters are selected for improved precision. SSA pretends the collective intellectual predatory behavior of sparrows [23]. The model separates sparrows into followers and discoverers. It dynamically seeks food resources, whereas followers attain food depending on the discoverers. Their individualities are switched, and they can all warn agents. Now, n signifies the number of sparrows, f denotes the fitness value, and d refers to the dimension.

$$X = \begin{bmatrix} x_1^1 & x_1^2 & \dots & x_1^d \\ x_2^1 & x_2^2 & \dots & x_2^d \\ \vdots & \vdots & \vdots & \vdots \\ x_n^1 & x_n^2 & \dots & x_n^d \end{bmatrix} \quad (11)$$

$$F_x = \begin{bmatrix} f([x_1^1 & x_1^2 & \dots & x_1^d]) \\ f([x_1^2 & x_2^2 & \dots & x_2^d]) \\ \dots \\ f([x_n^1 & x_n^2 & \dots & x_n^d]) \end{bmatrix} \quad (12)$$

With SSA, the discoverers offer predatory direction for every follower—the location upgrade equation for discoverers.

$$X_{i,j}^{t+1} = \begin{cases} X_{i,j}^t \cdot \exp\left(-\frac{i}{\alpha \cdot T_{max}}\right), R_2 < ST \\ X_{i,j}^t + R \cdot L, R_2 \geq ST \end{cases} \quad (13)$$

$X_{i,j}^t$ Indicates position in t iteration. α signifies an arbitrary number, and $\alpha \in (0,1]$. R denotes an arbitrary number. T_{max} Represents the maximal number of iterations. L denotes a matrix of 1xd. The value of every component is 1. R_2 depicts the warning value. ST indicates the safety value.

Now $R_2 < ST$, it indicates that no predators are found around the discoverer, it is relatively safe, and executes a broad array of searches. This strategy is not conducive to the diversity of the population. Conversely, combines a sine function and is based on the iteration counts. Its range of value gradually enlarges to increase the iteration counts. The consequence of this strategy exists in its capability to retain preceding optimum values, while concurrently improving either search range or diversity.

$$X_{i,j}^{t+1} = X_{i,j}^t \cdot \sin((\pi/2) * (1 - (t/T_{max}) * rand)) \quad (14)$$

While $R_2 \geq ST$ signifies that a predator is identified and an alert is delivered to another sparrow, who rapidly flees towards another safer place. Compared with the enhanced model, the enhanced model employs random numbers originating from a Cauchy distribution. It becomes evident that this improvement substantially widens either the value ranges or the search area.

$$X_{i,j}^{t+1} = X_{i,j}^t + Cauchy(0,1) \cdot L \quad (15)$$

The iterative equation directs position upgrades for discoverers using enhanced SSA.

$$X_{i,j}^{t+1} = \begin{cases} X_{i,j}^t \cdot \sin((\pi/2) * (1 - (t/T_{max}) * rand)), R_2 < ST \\ X_{i,j}^t + Cauchy(0,1) \cdot L, R_2 \geq ST \end{cases} \quad (16)$$

$$X_{i,j}^{t+1} = \begin{cases} R \cdot \exp\left(\frac{X_{worst}^t - X_{i,j}^t}{i^2}\right), i > \frac{n}{2} \\ X_p^{t+1} + |X_{i,j}^t - X_p^{t+1}| \cdot A^+ \cdot L, i \leq \frac{n}{2} \end{cases} \quad (17)$$

X_p^{t+1} indicates existing optimum positions recognized by discoverers, X_{worst}^t Signifies the worst position of the existing population globally. A is a matrix of 1xd, here its component

is arbitrarily distributed as 1 or -1, and $A^+ = A^T(AA^T)^{-1}$.

$$X_i^{t+1} = \begin{cases} X_{best}^t + \beta \cdot |X_i^t - X_{best}^t|, f_i \neq f_g \\ X_i^t + K \cdot \left(\frac{|X_i^t - X_{worst}^t|}{(f_i - f_w) + \varepsilon}\right), f_i = f_g \end{cases} \quad (18)$$

X_{best}^t Represents the existing global optimum location. β signifies an arbitrary number that succeeds a standard distribution with a variance of 1 and a mean of 0. f_i denotes the existing value of fitness, and f_g and f_w Refers to the existing global best and worst fitness values. And K indicates an arbitrary number among $[1, 1]$. ε indicates a very small constant.

$$X_i^{t+1} = \begin{cases} X_{best}^t + \delta \cdot |X_i^t - X_{best}^t|, f_i \neq f_g \\ X_i^t + K \cdot \left(\frac{|X_i^t - X_{worst}^t|}{(f_i - f_w) + \varepsilon}\right), f_i = f_g \end{cases} \quad (19)$$

The SSA originates an FF to attain greater classifier performance. It verifies a progressive value to demonstrate the enhanced outcome of the candidate solutions. The reduction of the classifier error rate is measured as the FF, as provided in Eq. (20).

$$\begin{aligned} fitness(x_i) &= ClassifierErrorRate(x_i) \\ &= \frac{\text{no of misclassified samples}}{\text{Total no of samples}} * 100 \end{aligned} \quad (20)$$

4. Experimental Validation

The performance validation of the BCHDL-SCMRE model is studied utilizing the Hospital Supply Chain database [24]. The database contains 500 diagnosis samples under four primary diagnoses, such as diabetes, fracture, appendicitis, and pneumonia, as shown below in Table 1. The no. of features is 10, but only 7 are selected.

Table 1. Details of the database

| Primary Diagnosis | Diagnosis Samples |
|-------------------|-------------------|
| Diabetes | 131 |
| Fracture | 133 |
| Appendicitis | 120 |
| Pneumonia | 116 |
| Total | 500 |

Figure 3 shows the classifier outcome of the BCHDL-SCMRE approach. Figures 3a and 3b display the confusion matrices with precise detection and classification of each class on 70:30. Figure 3c exhibits the PR inspection, denoting maximal performance on each class. At Last, Figure 3d elucidates the ROC inspection, exhibiting efficacious results with superior values of ROC for individual classes.

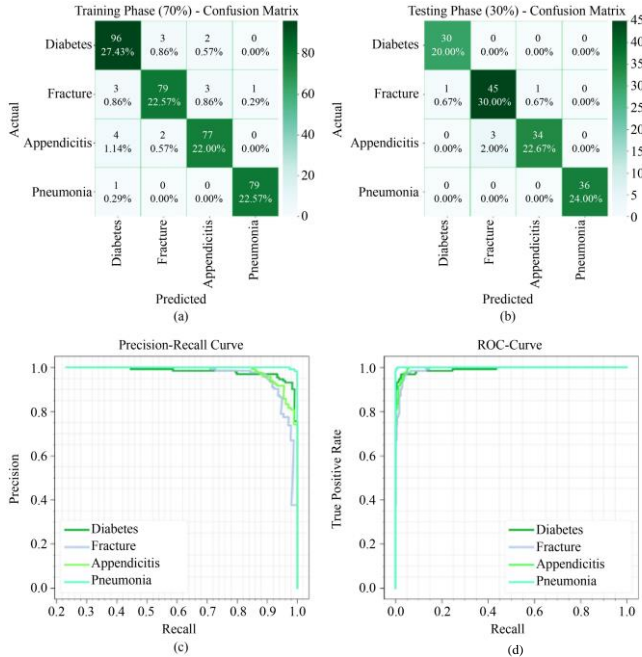


Fig. 3 Classifier outcome of (a-b) confusion matrix and (c-d) PR, and ROC curves

Table 2 and Figure 4 exemplify an average outcome of the BCHDL-SCMRE system on 70% TRPHE. The Diabetes class got $accu_y$, $prec_n$, $sens_y$, $spec_y$, and F_{Means} of 96.29%, 92.31%, 95.05%, 96.79%, and 93.66%, respectively. Likewise, the fracture class has got $accu_y$, $prec_n$, $sens_y$, $spec_y$, and F_{Means} of 96.57%, 94.05%, 91.86%, 98.11%, and 92.94%, respectively. In addition, the appendicitis class got $accu_y$, $prec_n$, $sens_y$, $spec_y$, and F_{Means} of 96.86%, 93.90%, 92.77%, 98.13%, and 93.33%, respectively. Finally, the pneumonia class got $accu_y$, $prec_n$, $sens_y$, $spec_y$, and F_{Means} of 99.43%, 98.75%, 98.75%, 99.63%, and 98.75%, respectively.

Table 2. Average values of the BCHDL-SCMRE model under 70% TRPHE

| Class Labels | Accuracy | Precision | Sensitivity | Specificity | F-Means |
|--------------------|--------------|--------------|--------------|--------------|--------------|
| TRPHE (70%) | | | | | |
| Diabetes | 96.29 | 92.31 | 95.05 | 96.79 | 93.66 |
| Fracture | 96.57 | 94.05 | 91.86 | 98.11 | 92.94 |
| Appendicitis | 96.86 | 93.90 | 92.77 | 98.13 | 93.33 |
| Pneumonia | 99.43 | 98.75 | 98.75 | 99.63 | 98.75 |
| Average | 97.29 | 94.75 | 94.61 | 98.16 | 94.67 |

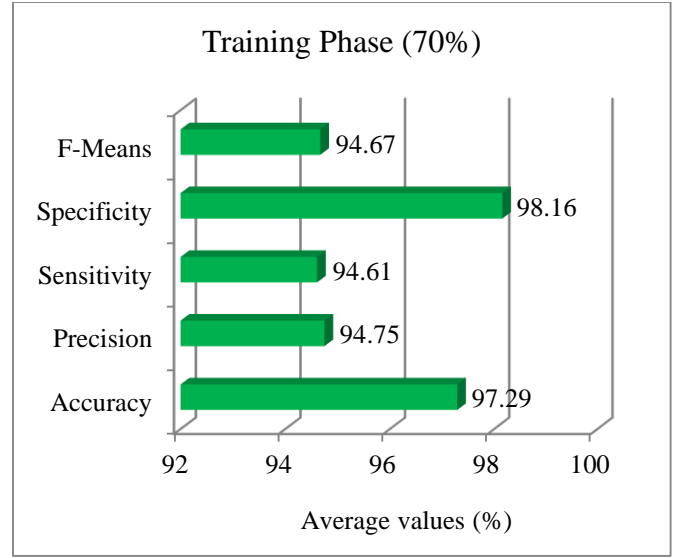


Fig. 4 Average values of the BCHDL-SCMRE model under 70% TRPHE

Table 3 and Figure 5 portray an average outcome of the BCHDL-SCMRE methodology at 30% TSPHE. The Diabetes class has attained $accu_y$, $prec_n$, $sens_y$, $spec_y$, and F_{Means} of 99.33%, 96.77%, 100.00%, 99.17%, and 98.36%, respectively. Similarly, the fracture class got $accu_y$, $prec_n$, $sens_y$, $spec_y$, and F_{Means} of 96.67%, 93.75%, 95.74%, 97.09%, and 94.74%, respectively. Moreover, the appendicitis class has achieved $accu_y$, $prec_n$, $sens_y$, $spec_y$, and F_{Means} of 97.33%, 97.14%, 91.89%, 99.12%, and 94.44%, respectively. Finally, the pneumonia class got $accu_y$, $prec_n$, $sens_y$, $spec_y$, and F_{Means} of 100.00%, 100.00%, 100.00%, and 100.00%, respectively.

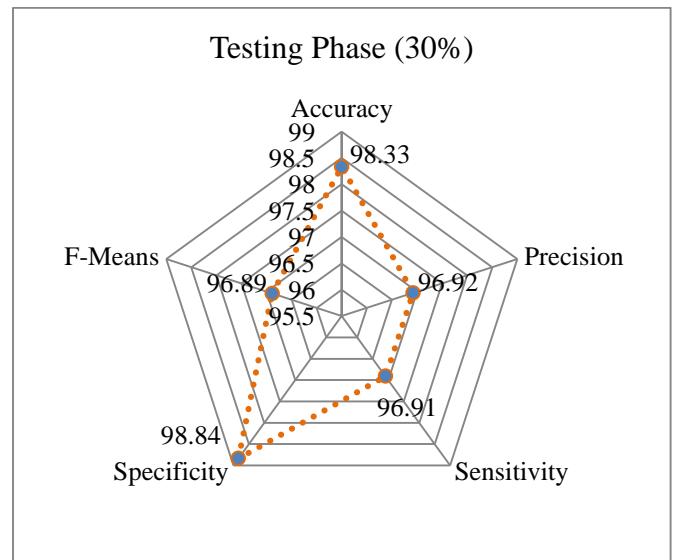


Fig. 5 Average values of the BCHDL-SCMRE model under 30% TSPHE

Table 3. Average values of the BCHDL-SCMRE model under 30% TSPHE

| Class Labels | Accuracy | Precision | Sensitivity | Specificity | F-Means |
|--------------------|--------------|--------------|--------------|--------------|--------------|
| TSPHE (30%) | | | | | |
| Diabetes | 99.33 | 96.77 | 100.00 | 99.17 | 98.36 |
| Fracture | 96.67 | 93.75 | 95.74 | 97.09 | 94.74 |
| Appendicitis | 97.33 | 97.14 | 91.89 | 99.12 | 94.44 |
| Pneumonia | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 |
| Average | 98.33 | 96.92 | 96.91 | 98.84 | 96.89 |

Figure 6 exemplifies the Training (TRAIN) $accu_y$ and Validation (VALID) $accu_y$ of a BCHDL-SCMRE method over 50 epochs. In the beginning, both TRAIN and VALID $accu_y$ Rise rapidly, denoting effective pattern learning from the data. Around the epoch, the VALID $accu_y$ Minimally exceeds the training accuracy, signifying good generalization without overfitting. As training advances, it reflects maximum performance and a minimum performance gap between TRAIN and VALID. The close alignment of both curves in training indicates that the method is well-regularized and generalized. This reveals the method's stronger capability in learning and retaining beneficial features across both seen and unseen data.

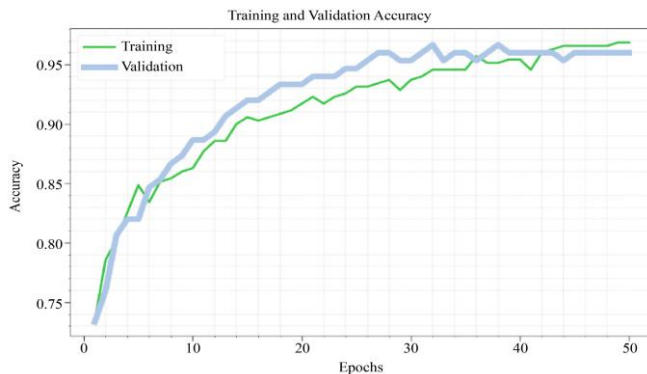
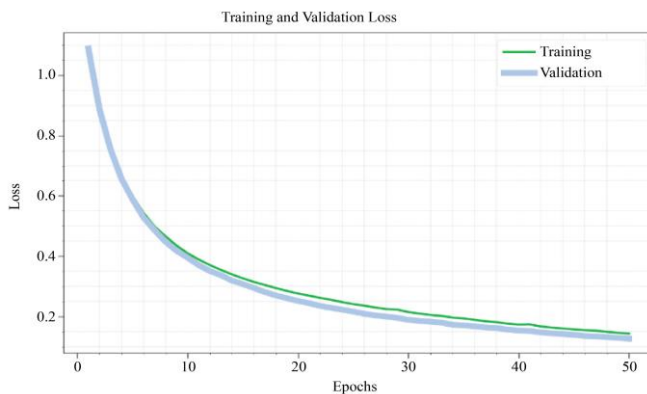
**Fig. 6 Accuracy curve of the BCHDL-SCMRE model****Fig. 7 Loss curve of BCHDL-SCMRE model**

Figure 7 illustrates the training and validation losses of the BCHDL-SCMRE approach across 50 epochs. The approach has a limited understanding of the material because TRAIN and VALID losses are high at the start. Both losses decrease over training, demonstrating that the technique is learning and refining. The TRAIN and VALID loss curves match throughout training, indicating that the algorithm has not overfitted and can generalize to novel data.

Figure 8 portrays the comparative analysis of the BCHDL-SCMRE methodology with existing classifiers [25-26]. The proposed BCHDL-SCMRE model got higher performance with $accu_y$, $prec_n$, $sens_y$, $spec_y$, and F_{Means} of 98.33%, 96.92%, 96.91%, 98.84%, and 96.89%, respectively. Whereas the present methodologies, namely KNN, LGBM, CNN-LSTM, GRU, RF-ranking-model, P-SVM-DT, and ML-with-MARCOS, got worse performance.

| | | | | | | |
|--------|--------------------|--|--------------|--------------|--------------|--------------|
| Models | KNN | 92.00 | 91.00 | 90.00 | 89.33 | 90.00 |
| | LGBM | 95.00 | 94.00 | 93.00 | 94.05 | 94.00 |
| | CNN-LSTM | 91.50 | 91.50 | 91.60 | 98.39 | 92.50 |
| | GRU | 98.13 | 97.82 | 84.53 | 97.48 | 97.30 |
| | RF-ranking-model | 94.00 | 89.25 | 93.81 | 95.03 | 92.82 |
| | P-SVM-DT | 92.00 | 90.82 | 96.37 | 91.11 | 96.35 |
| | ML-with-MARCOS | 95.00 | 94.49 | 90.20 | 93.93 | 96.14 |
| | BCHDL-SCMRE | 98.33 | 96.92 | 96.91 | 98.84 | 96.89 |
| | | Accuracy Precision Sensitivity Specificity F-Means | | | | |

Fig. 8 Comparative analysis of the BCHDL-SCMRE technique with existing models

Table 4 depicts the resources needed for primary diagnosis. For the Diabetes patient_ID, the P001 diagnosis needed 2 surgeons. While for Fracture patient_ID, the P003 diagnosis needed 1 nurse and 1 doctor. Whereas, for the Appendicitis patient_ID, the P005 diagnosis needed 2 surgeons. Meanwhile, for the Pneumonia patient_ID, the P037 diagnosis needed 1 nurse and 1 doctor.

Table 4. Resources needed for primary diagnosis

| Patient_ID | Primary_Diagnosis | Resources Needed |
|--------------|-------------------|-------------------|
| Diabetes | P001 | 2 Surgeons |
| Diabetes | P015 | 1 Nurse, 1 Doctor |
| Fracture | P003 | 1 Nurse, 1 Doctor |
| Fracture | P020 | 1 Nurse |
| Appendicitis | P005 | 2 Surgeons |
| Appendicitis | P011 | 1 Nurse, 1 Doctor |
| Pneumonia | P027 | 2 Surgeons |
| Pneumonia | P037 | 1 Nurse, 1 Doctor |

5. Conclusion

In this paper, a BCHDL-SCMRE model is developed in the Healthcare Industry. The objective of the article is to develop an intelligent and secure structure utilizing advanced methods to improve trust, transparency, and efficiency in SCM within the healthcare industry. To begin with, the BC technology is used in HSCM to guarantee security and transparency. Then, the Z-score normalization is used in the data preprocessing step for normalizing the input data. To pick

the best features, the FS process is implemented by the MRO algorithm. Besides, the hybrid of the TCN-GRU technique has been applied for the classification process. Eventually, the SSA is applied for parameter tuning to ensure that the optimal hyperparameters are selected for improved precision. To display the heightened performance of the proposed BCHDL-SCMRE system, a complete performance assessment is conducted. The comparative outcomes informed the improvised features of the BCHDL-SCMRE method.

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