Performance Assessment of Predictive Forecasting Techniques for Enhancing Hospital Supply Chain Efficiency in Healthcare Logistics

Manu R Dixit., Dr Sandeep Kumar Shivhare

Lnct University, Management Bhopal, India

DOI: https://doi.org/10.51244/IJRSI.2025.120800069

Received: 07 Aug 2025; Accepted: 12 Aug 2025; Published: 05 September 2025

ABSTRACT

The health care system is becoming too concerned about the acquisition of medications and medical equipment, collaboration with the wholesalers, the increased costs of their activity, and the management of the waste products. The nature (complex and non-linear) of the medical inventory requirements that are to be taken into account cannot be covered by the traditional rule-based or linear forecasting methodologies. The present study aims at optimizing hospital supply chain efficiency by evaluating the performance of forecasting methods that can be used to predict advanced forecasting. As part of preprocessing, the robustness of data was achieved by formatting the data type dates as datetimes, using one-hot encoding, and Min-Max normalization to gain quality data inputs using a real-world hospital supply chain dataset supplied by Kaggle. Hybrid-style deep learning (DL) of LSTM and GRU was implemented as a model to learn complex conditions within the supply-demand data series. Comparisons were carried out between this model and Gradient Boosting (GB), DBSCAN, K- Nearest Neighbors (KNN), and ARIMA to give a balanced analysis between supervised and unsupervised learning and time-series forecasting. The hybrid model, LSTM-GRU, performed the best having recorded an accuracy rate of 95.8% much higher than GB (94.30%), DBSCAN (92.7%), KNN (86%), and ARIMA (85%). Precision (95.6%), recall (95.1%), F1-score (95.8%) evaluated metrics and even the ROC (96%) further proved the efficacy of the model when processing supply-demand variability. This multi-model evaluation demonstrates the benefits of incorporating deep learning into healthcare logistics to provide data-based knowledge that may facilitate prompt inventory decision-making and contribute to better patient care outcomes. What this work emphasizes is the importance of predictive analytics in the creation of a more efficient, less costly, more patient-centric health infrastructure.

Keywords: Hospital Supply Chain, Healthcare Logistics, Inventory Forecasting, Supply Chain Optimization.

INTRODUCTION

The dynamic landscape in which health systems currently operate due to the digitalization process, the growth of interconnectedness, and enhanced reliance on data-driven logistics [1] presents health systems across the globe with a heavy burden of adjusting to a high-paced environment [1]. The use of technology in the logistics of the healthcare segment is now a necessity to ensure proper supply and distribution of vital treatment facilities and supplies. Healthcare logistics activities involve planning, procurement, distribution, management of medical supplies [2], pharmaceuticals, as well as healthcare services, to guarantee effective patient care and a functioning system. It is of critical importance to achieve compliance with the law of timely availability of resources, the reduction of shortages [3], and an improvement in general responsiveness of the healthcare system, particularly in emergencies (pandemics, natural disasters, or health crises). Effective logistics have a direct impact on patient outcomes, on operating efficiency, on health care sustainability [4].

Nevertheless, the global healthcare supply chain is still experiencing some persistent and emerging issues [5]. Stockouts and disruptions have occurred because of vulnerabilities in procurement systems, unpredictable patterns of demand and inefficiency in the logistics system. The supply chain fragility has also been contributed by climate change, world economic instability, manufacturer amalgamation, and geopolitical tensions [6]. Meanwhile, the healthcare systems are squeezed to reduce operational expenditure and attempt to exceed patient expectations and manage complicated stocks in various locations [7]. Also, the weak last-mile delivery, low research and development capabilities, and ineffective forecasting systems among other factors are the major contributors to operational bottlenecks. Another significant contributor to supply shortages specifically is poor demand forecasting that potentially leads to the entry of substandard medicines or counterfeit drugs into a health care system [8]. The inability to accurately predict the future is one of the most burning topics that not only makes it possible to end up with stockouts and overstocks but creates the risk that the system will start using counterfeit or expired medications.

Over the last few years, predictive forecasting has become a viable possibility for reducing such inefficiencies. Forecasting models allow healthcare organizations to predict future demands, achieve better distribution of their resources, and increase the visibility of supply chains by relying on historical data and using sophisticated analysis tools. Out of this, ML (machine learning) and DL models attracted significant popularity because they perform tasks with high- dimensional, non-linear, and time-dynamic information [9]. They both have become a disruptive solution in hospital supply chain management (HSCM). A subset of artificial intelligence (AI) [10] called ML algorithms can be employed to repeatedly discover trends and patterns in large datasets without explicit programming and apply these findings to make better predictions in the future [11]. Deep learning, an advanced branch of ML, utilizes artificial neural networks to handle complex, high-dimensional data, making it especially useful for capturing non-linear patterns in hospital supply chain datasets [12][13]. These models can be trained to accurately forecast demand for medical supplies, predict delays in medication delivery, and optimize inventory levels across multiple hospital units [14]. ML models can learn from historical trends to improve prediction accuracy, while DL architectures such as “GRU” and “LSTM” networks are specifically effective for handling temporal data in complex hospital logistics scenarios. This study focuses on assessing the performance of various predictive forecasting techniques, focusing particularly on predictive analysis-based forecasting models in ameliorating hospital supply chain efficiency. Through comparative evaluation using real-world hospital logistics datasets, this work seeks to identify which techniques offer the highest accuracy and reliability, thereby guiding data-driven decision-making and future innovations in healthcare logistics management.

Motivation and Contributions of the Study

The hospital supply chain due to its application in management of appropriate allocation of resources to manage hospitals efficiently should be efficient to provide essential medical resources in time, cost-effective operations, and a high standard of patient care. However, healthcare logistics often face challenges such as demand uncertainty, inventory shortages, and inefficient forecasting, which can lead to critical delays and increased waste. With the growing availability of healthcare data and advances in predictive analytics, there is a compelling need to explore and assess modern ML and DL techniques to enhance forecasting accuracy. This work is impelled by opportunity to harness these cutting-edge models to optimize supply chain operations, reduce inefficiencies, and support data-driven decision-making in healthcare systems, ultimately contributing to improved service delivery and patient outcomes. The following key summarization of this work is:

- The analysis is based on a publicly available hospital supply chain dataset from Kaggle, with data preprocessing steps such as datetime transformation, one-hot encoding, and normalization to corroborate consistency and quality of input data.

- This study brings forward a hybrid forecasting approach by combining LSTM and GRU architectures to effectively capture temporal patterns in hospital supply chain data and improve prediction accuracy.

- The work involves systematic comparisons of several methods of forecasting, such as Gradient Boosting, ARIMA, K-Nearest Neighbors (KNN) and DBSCAN and provides various considerations regarding predictive performance in healthcare logistics.

- The research achieves a coherent assessment platform by integrating supervised, unsupervised, and time-series forecasting techniques, which complement the general specificity and robustness of insights in various modeling paradigms.

- Major evaluation parameters given include F1-score, accuracy, recall, and precision, which are used to scrutinize outcomes of forecasting and determine the effectiveness of each models in controlling variability of healthcare supply and demand.

The above research is important to the extent that it can revolutionize the HSCM by incorporating the use of advanced predictive modeling forecasting methods. The research proves that deep learning in healthcare logistics is something to adopt by demonstrating the effectiveness of hybrid LSTM-GRU model in comparison to conventional machine learning and statistics. Since relevant patient care necessitates constant supply of medical supplies, proper planning and forecasting of medical supply demand is very pivotal to ensure it does not incur unnecessary wastages and reduce costs of operation. Not only does this work fill in an essential healthcare domain gap by meeting supply-demand uncertainty with a high degree of precision but also develops a scaling data-driven solution that can be adopted by healthcare institutions to maximize efficiency, responsiveness, and overall quality of service.

Organization of the Paper

The investigation is arranged as follows: Section II reviews related investigation on predictive forecasting techniques applied to hospital supply chains. Section III details the methodology, encompassing data collection, preprocessing, forecasting models, and evaluation metrics. The experimental findings and a comparison of the models' performances are shown in Section IV. Key findings are presented at the end of Section V, along with recommendations for further research.

LITERATURE REVIEW

This segment reviews contemporary advances in predictive forecasting techniques for hospital supply chains, highlighting AI and machine learning methods that enhance logistics efficiency, improve demand prediction, reduce stockouts, and support real-time decision-making in healthcare logistics through data-driven insights and automated inventory management systems. Selected recent studies are reviewed:

Okonkwo et al. (2025) impact of AI on ameliorating robustness and effectiveness of healthcare SCM in the US medical supply distribution system is examined in this research. According to important research, healthcare companies that use AI-powered supply chain systems report forecasting accuracy gains of up to 87% for predictive analytics models that can foresee supply chain interruptions. The study also demonstrates how automated decision support systems cut response times to supply chain interruptions by over 65%, while artificial intelligence (AI) technologies allow for 40% quicker recovery times during emergencies as compared to traditional techniques. However, the report highlights important issues such high implementation costs, data privacy problems, and the need for robust governance mechanisms [15]

Moreira et al. (2025) offer a thorough framework for using ML and advanced predictive analytics techniques to optimize healthcare SCM. This illustrates how the use of ensemble ML algorithms, particularly gradient-boosted decision trees and deep neural networks in a hybrid configuration, can lower inventory holding costs by 27.4% and predict demand fluctuations with 93.7% accuracy while preserving service levels above 98.5%. A novel stochastic optimization method that takes into consideration the particular limitations of hospital settings, such as perishability considerations and key item prioritization, is established using the mathematical modelling component. The effectiveness of the framework is confirmed by case studies conducted in three different healthcare systems, which show notable gains in operational indicators, such as a 42.3% drop in emergency procurement cases and a 31.8% decrease in stockout incidents [16]

Pabarja et al. (2024) develops a system for evaluating LARG in the hospital medical equipment supply chain in Iran, specifically in Hamadan. A particular group of medical equipment supply chain specialists additionally validated key indicators derived from a thorough literature research and other published publications in the field of LARG. According to the results, the medical equipment supply chain's LARG value is 0.787. Lower overall costs, improved control over inventories, shorter supply chain development cycle times, more new product introductions, information sharing amidst supply chain participants, pliable supply bases and sourcing, amortized use of fossil fuels, and the application of waste management techniques like recycling and reusing recyclable materials are some of the key indicators for assessing LARG in hospital medical equipment supply chain [17].

Kar et al. (2024) makes use of multi-task learning as it optimizes the execution of two interconnected tasks at the same time, such as the "shipped quantity" of medical supplies and their "actual days to delivery," greatly enhancing supply chain forecasts. By taking into account its importance in healthcare, the task "actual days to delivery" is better learnt than "shipped quantity" thanks to the prioritized multi-task learning with task-specific regularization. Furthermore, this task-specific regularization keeps the model from overfitting during training. In terms of forecasting both tasks, the findings and their analysis demonstrate a notable improvement of 0.3522 and 0.3531MAE and MSE. The proposed work outperforms the present work in terms of MAE, MSE, RMSE, and R-squared [18]

Thapa et al. (2023) new methodology for applying sophisticated AI forecasting models to ameliorate supply chain and inventory management in healthcare facilities is presented in this research study. The suggested method takes into consideration long-term epidemiological trends, emergency surges, and seasonal oscillations while effectively predicting demand patterns for essential medical supplies by combining deep reinforcement learning algorithms with multivariate time series analysis. Significant enhancements over traditional forecasting techniques were shown by their experimental implementation across a network of 17 metropolitan hospitals, including a 27% decrease in stock-out incidents, a 31% amortization in inventory carrying costs, and a 42% increase in prediction accuracy for specialized pharmaceutical supplies [19].

Mariappan et al. (2023) in order to tackle the urgent issue of forecasting when medications, diagnostics, and vaccinations will be sent during the ongoing COVID-19 epidemic, this study employs a unique artificial intelligence (AI) and ML technique. During COVID-19 epidemic, a big real-world e-pharmacy received over 3 million shipments of organic medicinal supplies, which were employed in this investigation. Using striped datasets of (source, destination, shipper) triplets, the researchers developed a range of machine learning multiclass stratification models. These models included RF (random forest), XRT(extra trees), DT (decision tree), MLP (multilayer perceptron), XGB (XGBoost), CB (Cat Boost), SGD (linear stochastic gradient descent), and NB (linear Naïve Bayes). According to the results, the turnaround time given by medicinal supply logistics companies is only 62.91% correct. On the other hand, the study's answer is up to 93.5% correct when compared to reality, which leads to an enhancement of up to 48.62%. Each week, there is a noticeable trend of more historical data and improved potentiality [20]

Table I summarizes prior studies on predictive forecasting in hospital supply chains, outlining methodologies, datasets, key findings, limitations, and future directions, with a focus on AI and machine learning approaches that enhance logistics efficiency, improve demand prediction, and support data- driven decision-making in healthcare logistics.

Table I. Summary of Existing Literature on Predictive Forecasting Techniques in Healthcare Supply Chains

Author (s)	**Methodology**	**Data**	**Key Findings**	**Limitation / Future Work**
Okonkwo et al. (2025)	Case analysis of AI systems in U.S. healthcare supply chains	U.S. medical supply distribution systems	AI improved forecasting accuracy up to 87% and 65% reduction in disruption response times	High implementation cost, data privacy concerns, and governance needs
Moreira et al. (2025)	Framework with ensemble ML (GBDT, DNN), stochastic modeling	Multi-dimensional data from 3 healthcare systems	93.7% accuracy in demand prediction, 27.4% cost reduction, 42.3% fewer emergency procurements	Requires scalable deployment, integration complexity across diverse systems
Pabarja	Fuzzy Inference	Hospital supply	LARG score = 0.787,	Does not directly

et al. (2024)	System (FIS) for LARG evaluation	chain data from Hamadan, Iran	identifies key LARG indicators (cost, time, waste, flexibility)	test forecasting techniques; model is static and regional
Kar et al. (2024)	Multi-task ML with task-specific regularization	Medical supply delivery data	Low MAE = 0.3522; accurate predictions of shipped quantity and delivery time	Focused only on two variables; real-time deployment not tested
Thapa et al. (2023)	Multivariate time series + Deep Reinforcement Learning	Data from 17 metropolitan hospitals	42% improvement in forecast accuracy, 27% fewer stock-outs	Organizational adaptation challenges and data integration barriers
Mariappan et al. (2023)	Ensemble stacking model zoo (RF, XGB, MLP, etc.)	3M+ real-worlde-pharmacy shipment records	93.5% accurate shipment time prediction, 48.6% better than logistics estimates	Focusedon e-pharmacy logistics; hospital applicability untested

METHODOLOGY

This performance assessment methodology presents a structured approach to evaluate predictive forecasting techniques aimed at improving supply chain efficiency in healthcare logistics. The workflow consists of the following key steps: (1) Dataset Acquisition from Kaggle, (2) Data Preprocessing and normalization, (3) Data Splitting into training and testing subsets, (4) ML-DL based Forecasting techniques, and (5) Model Evaluation using performance metrics. Figure 1 illustrates the overall workflow adopted in this study.

The following steps are discussed below for predictive forecasting in HSCM:

Data Collection and Visualization

The first step of performance assessment methodology data collection. The Hospital Supply Chain dataset provides a detailed view of hospital inventory management and healthcare logistics processes, capturing both operational variables and procurement details. The dataset consists of 500 rows and 11 columns with features such as Date, Item_ID, Item_Type, Item_Name, Current_Stock, Min_Required, Max_Capacity, Unit_Cost, Avg_Usage_Per_Day, Restock_Lead_Time, and Vendor_ID. The data enables performance assessment and predictive modeling to optimize supply chain efficiency helping hospitals forecast demand, manage inventory, reduce stockouts, streamline vendor relationships, and ultimately ensure timely accessibility of medical supplies and equipment. This dataset is aligned with the widely used Hospital Supply Chain dataset available on Kaggle, healthcare logistics optimization.

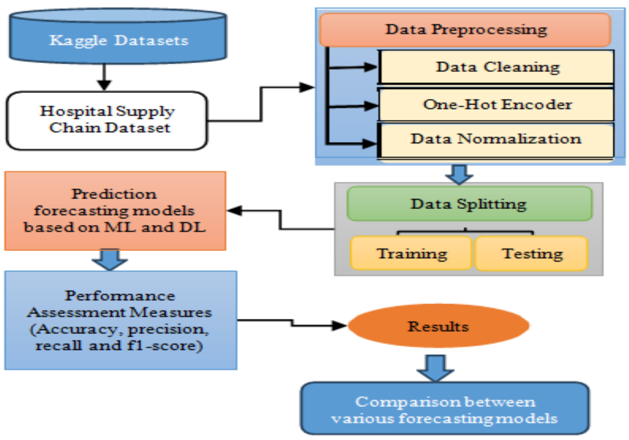

Fig. 1. Performance assessment methodological procedure for predictive forecasting in HSCM

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XII Issue VIII August 2025

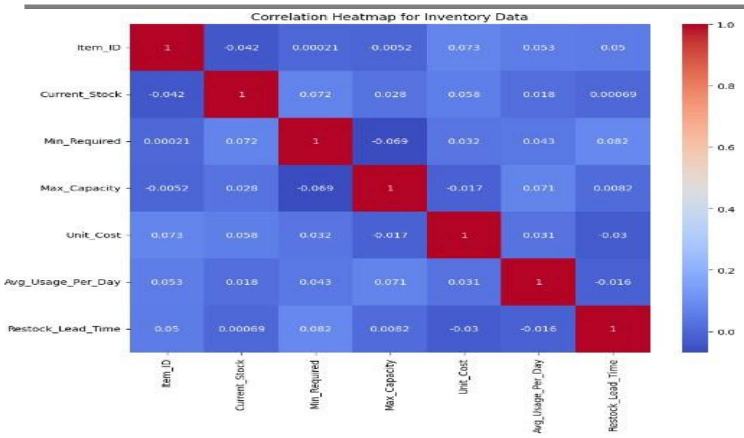

Fig. 2. Correlation Heatmap of the Dataset

Pearson correlation coefficients between important inventory parameters, including "Current_Stock," "Min_Required," "Max_Capacity," "Unit_Cost," "Avg_Usage_Per_Day," and "Restock_Lead_Time," are displayed in the correlation heatmap in Figure 2. The intensity and direction of correlations are shown by a red-to-blue gradient, where white denotes weak or no connection, blue denotes strong negative correlation, and red denotes high positive correlation. Perfect self-correlation is displayed by diagonal elements (value = 1). The heatmap reveals, for instance, a moderate positive correlation amidst 'Min_Required' and 'Current_Stock', while 'Unit_Cost' shows weak correlation with most features. This concise overview helps uncover data relationships useful for inventory monitoring and planning.

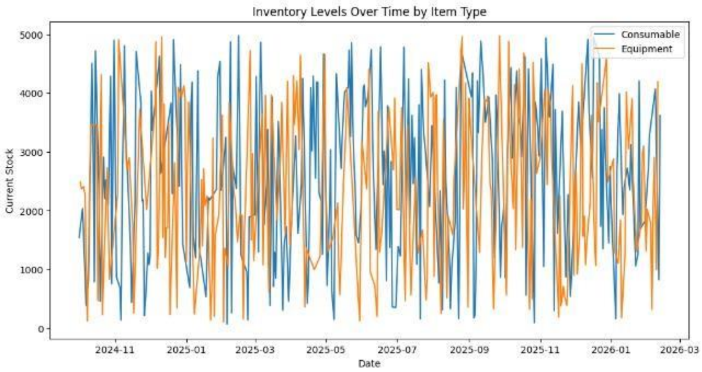

Fig. 3. Inventory Levels Over Time by Item Type

Figure 3 shows the inventory levels over time, plotting "Current Stock" (y-axis) against "Date" (x-axis) for two item types: "Consumable" (blue line) and "Equipment" (orange line). The x-axis spans from late 2023 to early 2026, showing a time series of inventory fluctuations. Both item types exhibit highly volatile stock levels, with frequent and significant changes ranging from nearly 0 to approximately 5000 units. Rather than following a clear long-term trend, the data reveals continuous, sharp variations in stock, indicating a dynamic inventory system influenced by shifting operational demands or supply conditions.

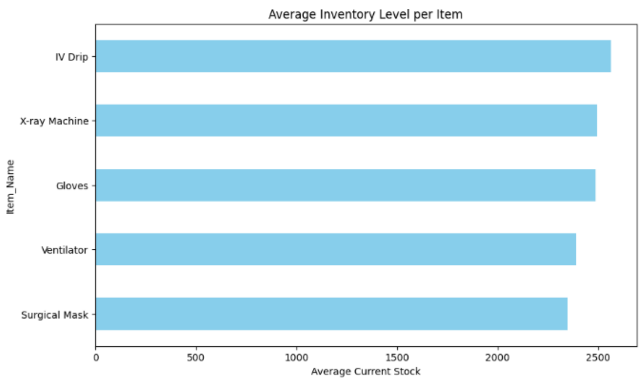

Fig. 4. Average Inventory Level per Item

The horizontal bar chart the average current stock for five specific medical items in Figure 4. The y-axis lists the "Item_Name": 'IV Drip', 'X-ray Machine', 'Gloves', 'Ventilator', and 'Surgical Mask'. The x-axis instantiates "Average Current Stock," ranging from 0 to 2500. All bars are a light blue color. 'IV Drip', 'X-ray Machine', and 'Gloves' have the highest average inventory levels, all appearing to be just above 2500 units. 'Ventilator' has an average stock level slightly below 2500, and 'Surgical Mask' has the lowest average stock among the listed items, around 2300–2400 units. The figure supports understanding of inventory distribution and helps prioritize stock management of medical items.

The distribution of key inventory features using box plots, highlighting data spread, central values, and outliers sown in Figure 5. Features like 'Current_Stock' and 'Max_Capacity' center around 3000–4000 units, while 'Unit_Cost' has a broader range. 'Restock_Lead_Time' mostly falls between 5 and 20 days. These plots help reveal patterns, variability, and potential anomalies across the dataset.

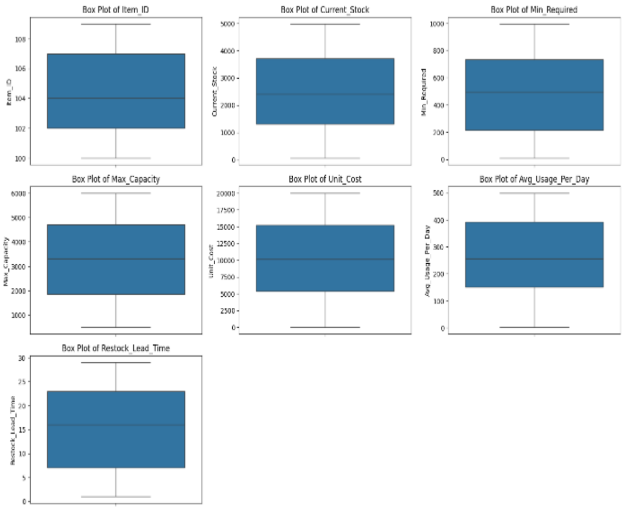

Fig. 5. Box Plot Visualization of Feature Distributions

Data Preprocessing

Pivotal step in building and implementing ML models is Data pre-processing. It assists in corroborating that input data is clear, consistent, and formatted correctly, which enables the model to identify trends and produce precise predictions on fresh, untested data. The preprocessing phase involved the following steps:

1) Convert the Date Column to Datetime Format:

To support the Date column was first converted to datetime format using pd.to date time (). From it, key temporal features were extracted: Month (month name), Year, Days (day name), and Month Date (day of month). The features augment time-based insights.

2) One-Hot Encoder for Data Encoding

The One Hot Encoder changed the categorical variable and boosted the performance of the representation of large numbers of categories. The steps led to the production of binary features that recorded the precise nature or scenarios that were involved in each category. Such attributes provided useful insight into consumer behaviour. The initial features that were encoded were then combined to create a composite feature set putting consideration on both numerical and categorical factors.

3) Max-Min Normalization

Normalization was important to avoid the domination of features with higher magnitudes on ones with low values [21]. The normalization that has been utilized in this study is the min-max normalization which assigns the values of all features a range between 0 and 1. Equation (1) gives the formula of this method:

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XII Issue VIII August 2025

Predictive Forecasting Models

This subsection can give the history of SCM(supply chain management) predictive forecasting models in healthcare industry using ML and DL models.

4) Long Short-Term Memory (LSTM)

A recurrent neural network with three gates is called an LSTM. These include input, output, and forget gates. In traditional RNNs, the gradient vanishes due to the LSTM's vanishing gradient approach. One important consideration when deciding whether to keep or remove previously learnt knowledge is the forget gate. Figure 6 presents the LSTM model architecture.

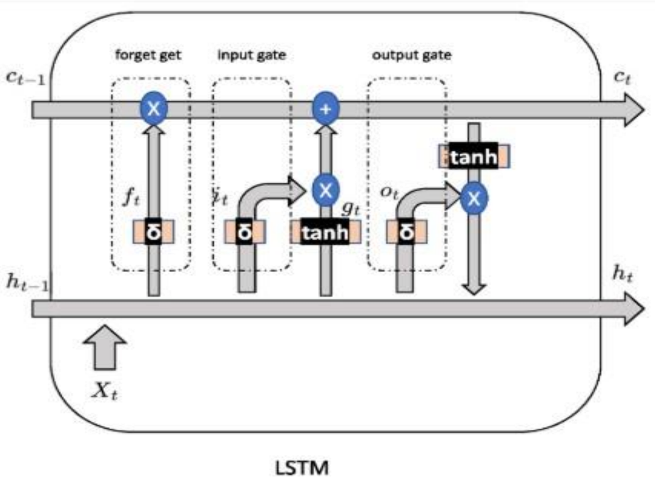

Fig. 6. Architecture of LSTM

It determines whether to retain or remove data from cell state of prior time step based on an evaluation of its relevance. The calculation for the forget gate is shown in Equation (2):

$$f_t = \sigma(W_f \, . \, [h_{t-1}, x_t] + b_f) \qquad (2)$$

Similarly, input gate determines which new values should be modified by processing previous output (h_{t-1}) and current input (x_t). It uses a weight matrix W_i, a sigmoid function σ, and a bias term b_i, generating a candidate value for the current cell state C_t as displayed in Equation (3):

$$i_t = \sigma(W_i . [h_{t-1}, x_t] + b_i) \qquad (3)$$

The candidate cell state value C_t is calculated utilizing hyperbolic tangent function as shown in Equation (4):

$$C_t = tanh(W_c \, . \, [h_{t-1}, x_t] + b_c) \qquad (4)$$

The modified cell state C_t amalgamates forget gate output

f_t, the previous cell state C_{t-1}, the input gate output i_t, and new candidate state C_t as displayed in Equation (5):

$$X_{normalized} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

$$C_t = f_t * C_{t-1} + i_t * C_t \qquad (5)$$

The output gate then ascertain how much the cell state

where X_{min} and X_{max} represent the data feature's lowest and highest values, respectively, and X represents the data feature's current value.

Data Splitting

To examine the usefulness of the model, the data had to be segregates into training and testing sets and in this case, 80 percent of dataset was allocated to training and determining the parameters and the other 20 percent was reserved to test and assess the potentiality of generated model.

should affect current output. The output o_t is calculated using a sigmoid function, and the final output h_t is derived by applying hyperbolic tangent function to current cell state and scaling it by the output gate value depict in Equations (6-7):

$$o_t = \sigma(W_o . [h_{t-1}, x_t] + b_o) \qquad (6)$$

$$h_t = o_t * \tanh(C_t) \qquad (7)$$

The ReLU activation function is used in the fully linked layer of LSTM model.

Gated Recurrent Unit (GRU)

To resolve problem of exploding or vanishing gradients, the GRU was created. It is an improved LSTM model that controls information flow using gate structures as well[22]. It's crucial to keep in mind that since GRU lacks an output gate, anyone can access any data. Figure 7 illustrates how the input and forget gates are amalgamated in LSTM, However, GRUs only have two gates: reset and update.

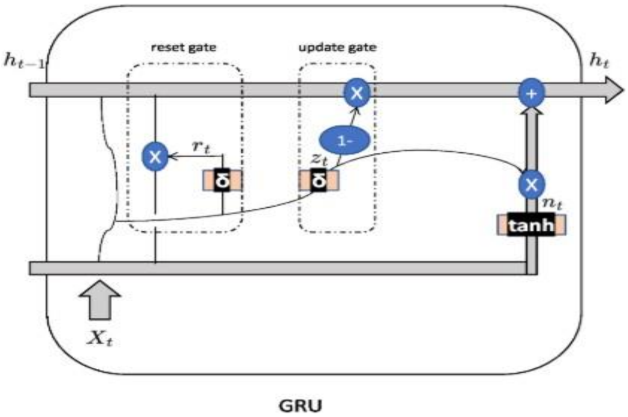

Fig. 7. Architecture of the Gated Recurrent Unit

GRUs has better potentiality as they have limited parameters and a simpler structure. GRU reset and update gates are represented by Equations (8) to (11) as follows:

$$r_t = ([h_{\{t-1\}}, x_t] + U_r h_{\{t-1\}} + b_r) \qquad (8)$$

$$z_t = ([h_{\{t-1\}}, x_t] + U_z h_{\{t-1\}} + b_z) \qquad (9)$$

$$(\hat{h}) = \tanh(W\ [r * h\ , x\ ] + b\ ) \qquad (10)$$

- **Gradient Boosting (GB):** GB is a versatile exploitative ensemble ML method that constructs predictive models as a series of imperfect learners, or weak learners-most often, decision trees. Each tree attempts to correct the errors of its predecessor, minimizing the overall prediction error. GB is highly effective in capturing complex patterns in structured hospital logistics data, especially for forecasting tasks [23].

- **Density-Based Spatial Clustering of Applications with Noise (DBSCAN):** DBSCAN is an unsupervised clustering technique that labels points that are isolated in low-density areas as outliers and clusters together points that are densely packed. In healthcare logistics, it can help in identifying abnormal demand patterns or segmenting regions with similar supply chain behavior, aiding in targeted forecasting strategies [24].

- **K-Nearest Neighbors (KNN):** KNN is a straightforward, non-parametric classification and regression procedure that uses the average or majority of the new data points' "k" nearest neighbors in the training dataset to determine their values. In the context of hospital supply chains, KNN can be used to predict demand levels by comparing them with similar historical scenarios [25].

- **Auto Regressive Integrated Moving Average (ARIMA):** ARIMA is a classical time series forecasting technique that amalgamates autoregression, differencing (integration), and moving averages to model linear dependencies in past values. It is particularly suitable for univariate time series data, such as historical inventory levels or patient inflow, t h t

$\{t-1\}$ t h and is used to forecast future trends in hospital supply

$$h_t = (1 - z_t) * h_{\{t-1\}} + z_t * (\hat{h}_t) \quad (11)$$

Where $r_t$is reset gate at time step t.$z_t$is update gate at time step t.$h_{\{t-1\}}$ is hidden state at time step t-1, $x_t$is input at time step t. σ is sigmoid activation function, W is weight matrix for interpolation calculation. b is bias label for interpolation calculation. h_t is hidden state at time step t.

Hybrid LSTM-GRU Model training:

In this study, a hybrid deep learning approach was adopted by configuring and training two sequential models, LSTM and GRU, using TensorFlow Keras' Sequential API to enhance predictive accuracy in construction-related outcomes. Both models followed a similar architecture, each comprising two recurrent layers with 100 and 50 units respectively, and incorporated L2 regularization (penalty coefficient of 0.01) to mitigate overfitting. The final prediction stage was performed and demand [26].

Performance Metrics

In ML, evaluation metrics are crucial for quantifying model performance. It gives a quantitative value of model performance in terms of a count of measures: recall, ROC- AUC, F1 score, accuracy and precision. The metrics assist the researchers in selection of most appropriate approach to a specific task and, therefore, guarantee the appropriateness of the model that they select or follow.

Accuracy

The percentage of accurately anticipated cases serves as an indicator of accuracy [27]. Despite its utility it is also unreliable because imbalanced data sets can cause high accuracy to attribute too much weight to performance on the prevalent class which it is specified in Equation (12).

by dense layer with linear activation and L2 regularization. The choice of the combination of the LSTM and GRU architectures was based on large amounts of experimentation

Precision

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (12)$$

to enable the balance of model complexity and performance. The "Adam optimizer" was used and "learning rate" of 0.001 made the best models have a stable learning process since the loss function rapidly varied. The training was done within 50 epochs at a batch size of 256 and an early stopping mechanism

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XII Issue VIII August 2025

It measures relative number of true positives of all the predicted positives, and is especially emphasized when a small count of false positives is critical. It is elucidated as in Equation (13).

was used that interrupted the training process when the validation loss failed to amortize in 10 consecutive epochs with best weights being restored. This combination of

5) *Recall*

$Precision = \frac{TP}{}$

$TP+FP$ (13)

networks was a careful attempt to exploit the benefits of both LSTM and GRU models in order to produce solid and inaccurate forecasts with a low probability to resulting in training instability and overfitting.

It is the ratio of correctly counted positives; this is important to use when false negatives should be kept to a minimum and is written in Equation (14).

6) *F1-score*

$Recall = \frac{TP}{}$

$TP+FN$ (14)

while validation loss dropped from 0.9 to around 0.2, indicating effective learning with minimal overfitting. Simultaneously, the training accuracy improved consistently, F1-score is the average of accuracy and recall, and can dynamically strike an optimum balance between false negatives, and false positives. It is found as in Equation (15).

$2\ (Precision \times Recall)$

rising from approximately 60% to 96.5%, and the validation accuracy increased from around 85% to 95.8%. The close alignment of both loss and accuracy curves for training and validation sets confirms that the model generalizes well and

7) *ROC Curve*

$F1\ Score = \underline{\qquad\qquad}$

$Precision \times Recall$ (15)

maintains stability, achieving high predictive performance in the hospital supply chain forecasting.

A graphical representation of the ROC (Receiver Operating Characteristic) is a plot of TPR (True Positive Rate) against FPR(False Positive Rate) which permits one to observe the trade-off amidst the sensitivity and specificity at different threshold so settings. Better performance is shown by a model that has a curve that is relatively closer to top-left corner.

Collectively, the evaluation measures provide an in-depth understanding of the model capacity to make the right predictions.

RESULT ANALYSIS AND DISCUSSION

This paper will evaluate how efficient advanced predictive forecasting models can be used to optimize the hospital supply chain, and especially the healthcare logistics. Table II presents the metrics on evaluation of the Hybrid LSTM-GRU model and the Gradient Boosting (GB) model to forecast in HSCM. LSTM-GRU model has been

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XII Issue VIII August 2025

superior to GB model regarding their main performance indicators. It attains success of 95.8% and 94.3 on GB which proves that it has an increased level of correct predictions. Regarding accuracy, LSTM-GRU achieves a score of 95.6 which is slightly higher than GB of 94.89, which is better in eliminating false positives. The recall measure value of LSTM-GRU at 95.1% compared to the GB result of 94.16 more accurately indicates the ability to detect the true positive cases. Moreover, the F1 score that amalgamates both recall and precision is 95.8 of LSTM-GRU which once more outstrips 94.12 obtained by GB. This finding proves that the LSTM-GRU model was better at predicting and perfectly fit complex healthcare chain conditions.

Table II. Evaluation metrics of lstm-gru and gradient boosting models for healthcare supply chain

Metrics	LSTM-GRU	Gradient Boost (GB)
Accuracy	95.8	94.30
Precision	95.6	94.89
Recall	95.1	94.16
F1 Score	95.8	94.12

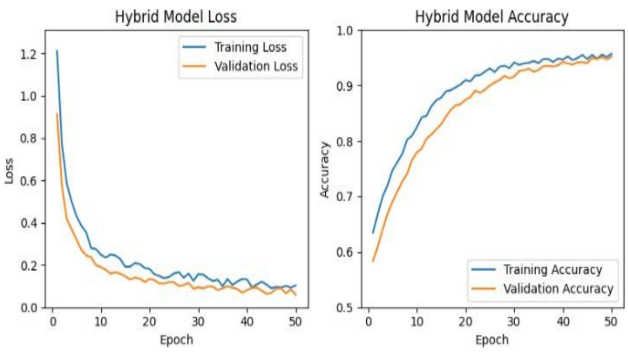

Fig. 8. Training and Validation loss curve of Hybrid LSTM-GRU

Figure 8 delineates training and validation loss and accuracy curves of DL model used to forecast the hospital supply chain developed using more than 50 epochs. As shown, the training loss gradually decreased from nearly 1.1 to 0.15,

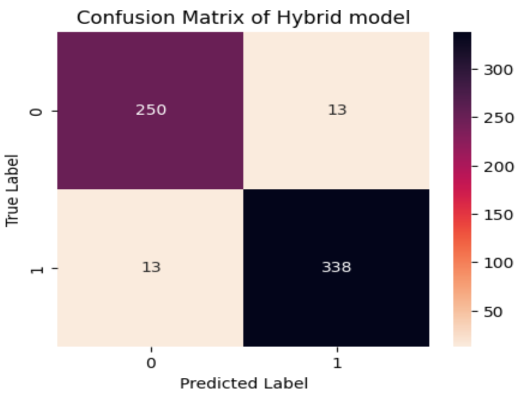

Fig. 9. Confusion matric of Hybrid LSTM-GRU for hospital supply chain forecasting

Figure 9 presents the confusion matrix of the Hybrid LSTM-GRU model applied to hospital supply chain forecasting. Out of 263 actual instances of class '0', the model accurately predicted 250 and misclassified 13. For class '1', comprising 351 actual instances, the model correctly identified 338 and misclassified 13. These results reflect the model's strong performance, showcasing high accuracy in distinguishing between both classes and a robust capability in identifying true positives and true negatives.

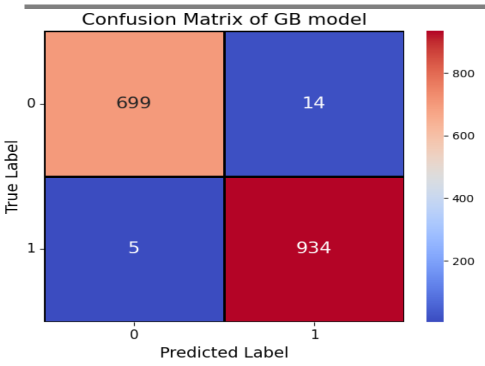

Fig. 10. Confusion matric of GB for hospital supply chain forecasting

Based on the provided confusion matrix for the Gradient Boosting (GB) model shows in Figure 10, its performance in hospital supply chain forecasting. The matrix shows a total of 713 actual instances of class '0' (699+14), out of which the model correctly identified 699, while incorrectly classifying 14 as class '1'. Among the 939 actual class 1 instances(5+934), 934 were correctly classified whereas 5 were misclassified as class 0. These values denote that GB model is extremely accurate to both classes in its prediction. This is indicated by a low false positive (14) and false negative (5) reading indicating an effective, reliable and robust forecasting performance since the model is able to correctly differentiate the two classes with minimal errors. Such performance makes the GB model an effective contender of the forecasting activity.

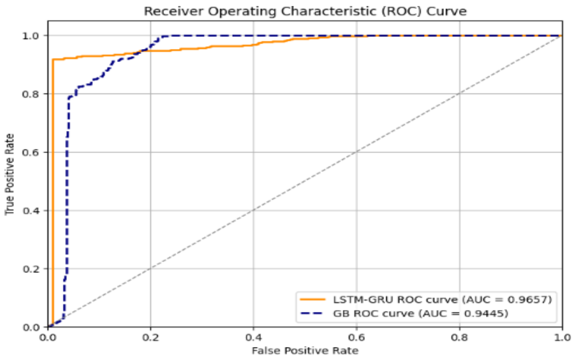

Fig. 11. ROC Curve Comparison Between LSTM-GRU and GB models

Figure 11 shows the comparison of ROC curves of the LSTM-GRU and the GB models showing the performance of the former and the latter on the classification task. The solid orange line denoting LSTM-GRU model has bigger AUC value of 0.9657, which shows that this model performs better than the GB model in differentiating amidst positive and negative classes. The AUC of the GB model, which is shown in a dashed navy blue line, is a bit lower at 0.9445. The given models have high results, and their curves are substantially above a dashed diagonal line which can simulate a random classifier. Nonetheless, the curve of the LSTM-GRU model is always near the top-left corner of plot and indicative of a higher true positive when compared to the false positive rate. This implies that the LSTM-GRU model would better at correctly predicting positive events and ensuring that false positive cases are few implying that it is more effective at the particular application in comparison to the GRU-LSTM model.

Comparative Study

In this segemnt, a comparative scruntinize will be carried out of predictive forecasting methods that will be used to achieve what is considered as an efficient supply chain of a hospital. Table III shows the accuracy profile of various predictive forecasting models used in hospital supply chain optimization. The Hybrid LSTM-GRU model closely follows with an accuracy of 95.8 % indicating that it best fits to pick out the complex temporal patterns in data. The second most appropriate model comes after this one, and it is the Gradient Boosting (GB) model, which has 94.3%. Though it is not optimal in comparison to the first model, it also performs well as it is a model of ensemble learning. At 92.7 accuracy rate, DBSCAN is a fairly effective unsupervised clustering algorithm. Such traditional models perform very poorly, however, such as K-Nearest

Neighbors (KNN) and ARIMA, being 86 percent and 85 percent, respectively. The two results indicate the paramount performance of deep learning and ensemble techniques to classical statistical and clustering methods in precise forecasting and optimization of hospital supply chain operations.

Table Iii. Accuracy Comparison Of Predictive Forecasting Models For Hospital Supply Chain Optimization

Model	Accuracy
LSTM-GRU	95.8
GB	94.30
DBSCAN[24]	92.7
KNN[25]	86
ARIMA[26]	85

The hybrid LSTM-GRU approach had significant superiority as a forecasting model of performance measures in the optimization of a supply chain in hospitals compared with the traditional machine learning technique and statistical models. Its capability to trap intricate temporality as well as the orderly dependence made it provide better credible forecasts which were necessary in making preactive decisions. The LSTM-GRU model had a higher rate of prediction accuracy and classification power compared to other models such as Gradient Boosting, DBSCAN, KNN, and ARIMA. This effectively shows that it can be effective not just in the modeling of non-linear trends but also in its ability to model performance stability making it one of the most appropriate fit in real life scenarios of modeling healthcare logistics.

CONCLUSION AND FUTURE SCOPE

The ability to perform predictive forecasting also greatly helps improve the effectiveness of hospital supply chains through better logistics, resource planning, and operation decision-making related to healthcare. The proposed study regards the solution of deep learning that can help solve the ongoing issues in hospital chains management focusing on the precision of the demand forecast and the operational efficiency. The hybrid LSTM-GRU model had best efficacy accuracy of 95.8% which was improved over the traditional models in forecasting inventory needs and limiting disruption of supply. To make the comparative analysis, LSTM-GRU model was evaluated besides the recognized approaches Gradient Boosting (GB), DBSCAN, K-Nearest Neighbors (KNN) and ARIMA. In spite of its good performance, the study has its limitations. Also, the LSTM-GRU can pose hardware requirements that would be troublesome to implement in resource-limited healthcare facilities.

Nonetheless, despite the great results of the LSTM-GRU forecasting model, there are a number of limitations. The quality and the amount of time-series data are of crucial importance in the effectiveness of the model, and the latter does not fit well into dynamic environments in real-time applications. Also, training time and the computational cost may be high. The next step will be a possible extension of the model to datasets consisting of multiple hospitals, the involvement of real-time external factors, like pandemics or supply chain disruptions and interpretability, using explainable AI approaches, such as SHAP and LIME. The accuracy, flexibility, and scalability in complicated healthcare settings will also be enhanced by trying out further additional models like the XGBoost, Bi-LSTM, and Transformer-based architectures.

REFERENCES

1. W. Alice, “Zero Trust Architecture in Public Health Systems A Cybersecurity Blueprint for Healthcare Logistics,” no. July, 2025.
2. S. Pandya, “Predictive Modeling for Cancer Detection Based on Machine Learning Algorithms and AI in the Healthcare Sector,” *TIJER - Int. Res. J.*, vol. 11, no. 12, pp. 549–555, 2024.

3. M. L. McBride, “Predicting Vulnerabilities in the Delivery of Secure Healthcare Supply Chain Services,” *Cybersecurity Innov. Technol. J.*, vol. 2, no. 1, pp. 26–40, 2024, doi: 10.53889/citj.v2i1.340.
4. S. Pandya, “Integrating Smart IoT and AI-Enhanced Systems for Predictive Diagnostics Disease in Healthcare,” *Int. J. Sci. Res. Comput. Sci. Eng. Inf. Technol.*, vol. 10, no. 6, Dec. 2024, doi: 10.32628/CSEIT2410612406.
5. J. Thomas, “Enhancing Supply Chain Resilience Through Cloud- Based SCM and Advanced Machine Learning: A Case Study of Logistics,” *J. Emerg. Technol. Innov. Res.*, vol. 8, no. 9, pp. 357– 364, 2021.
6. V. Singh, “AI-Driven ERP Evolution: Enhancing Supply Chain Resilience with Neural Networks and Predictive LSTM Models,” *Eur. J. Adv. Eng. Technol.*, vol. 12, no. 2, pp. 47–52, 2025.
7. V. Alemede, “Deploying Strategic Operational Research Models for AI-Augmented Healthcare Logistics, Accessibility, and Cost Reduction Initiatives,” *Int. Res. J. Mod. Eng. Technol. Sci.*, no. February, 2025, doi: 10.56726/irjmets67609.
8. M. Seyedan and F. Mafakheri, “Predictive big data analytics for supply chain demand forecasting: methods, applications, and research opportunities,” *J. Big Data*, 2020, doi: 10.1186/s40537- 020-00329-2.
9. S. P. Kalava, “The Role of AI in Reinventing Hospitality Safety Measures After COVID-19,” *J. Artif. Intell. Cloud Comput.*, vol. 3, no. 1, pp. 1–3, Feb. 2024, doi: 10.47363/JAICC/2024(3)E153.
10. S. A. Pahune, “A Brief Overview of How AI Enables Healthcare Sector Rural Development,”2024, doi: 10.13140/RG.2.2.16675.63525.
11. A. I. Bilal, U. S. Bititci, and T. G. Fenta, “Challenges and the Way Forward in Demand-Forecasting Practices within the Ethiopian Public Pharmaceutical Supply Chain,” *Pharmacy*, vol. 12, no. 3, 2024, doi: 10.3390/pharmacy12030086.
12. V. Prajapati, “Enhancing Supply Chain Resilience through Machine Learning-Based Predictive Analytics for Demand Forecasting,” *Int. J. Sci. Res. Comput. Sci. Eng. Inf. Technol.*, vol. 11, no. 3, 2025, doi: 10.32628/CSEIT25112857.
13. K. Murugandi and R. Seetharaman, “Analysing the Role of Inventory and Warehouse Management in Supply Chain Agility : Insights from Retail and Manufacturing Industries,” *Int. J. Curr. Eng. Technol.*, vol. 12, no. 6, pp. 583–590, 2022.
14. I. M. Hezam, A. M. Ali, A. M. Alshamrani, X. Gao, and M. Abdel- Basset, “Artificial intelligence’s impact on drug delivery in healthcare supply chain management: data, techniques, analysis, and managerial implications,” *J. Big Data*, vol. 11, no. 1, 2024, doi: 10.1186/s40537-024-01049-7.
15. F. C. Okonkwo, B. G. Akonor, and T. K. Adukpo, “Artificial Intelligence in Healthcare Supply Chain Management: Enhancing Resilience and Efficiency in U.S. Medical Supply Distribution,” *EPRA Int. J. Econ. Bus. Manag. Stud.*, vol. 12, no. 1, pp. 285–291, Jan. 2025, doi: 10.36713/epra19901.
16. T. Moreira and C. Siqueira, “Improving Healthcare Supply Chain Efficiency through Predictive Analytics and Machine Learning: A Data-Driven Management Framework,” *North. Rev. Algorithmic Res. Theor. Comput. Complex.*, vol. 10, no. 5, pp. 1–18, 2025.
17. R. Pabarja, G. Jamali, K. Salimifard, and A. Ghorbanpur, “Analysis of the LARG of the hospital medical equipment supply chain using the fuzzy inference system,” *Int. J. Res. Ind. Eng.*, vol. 13, no. 2, pp. 116–151, 2024.
18. S. Kar, M. K. Mohanty, and P. K. G. Thakurta, “Efficient healthcare supply chain: A prioritized multi-task learning approach with task-specific regularization,” *Eng. Appl. Artif. Intell.*, vol. 133, Jul. 2024, doi: 10.1016/j.engappai.2024.108249.
19. K. Thapa and M. Poudel, “AI-Based Forecasting Models for Inventory and Supply Chain Optimization in Healthcare Facility Management,” *Int. Rev. Exp. Sci. Sci. Discov. Technol. Adv.*, vol. 7, no. 10, pp. 1–12, 2023.
20. M. B. Mariappan, K. Devi, Y. Venkataraman, M. K. Lim, and P. Theivendren, “Using AI and ML to predict shipment times of therapeutics, diagnostics and vaccines in e-pharmacy supply chains during COVID-19 pandemic,” *Int. J. Logist. Manag.*, 2023, doi: 10.1108/IJLM-05-2021-0300.
21. A. Dixit, S. Routroy, and S. K. Dubey, “A systematic literature review of healthcare supply chain and implications of future research,” *Int. J. Pharm. Healthc. Mark.*, vol. 13, no. 4, pp. 405– 435, 2019.
22. E. Turki, “Management and optimization of the life of spare parts: The case of a healthcare closed-loop supply chain,” 2024.

23. C. Bentéjac, A. Csörgő, and G. Martínez-Muñoz, "A comparative analysis of gradient boosting algorithms," *Artif. Intell. Rev.*, 2021, doi: 10.1007/s10462-020-09896-5.
24. A. E. Khedr, Y. S. Alsahafi, and A. M. Idrees, "A Proposed Multi- Level Predictive WKM_ID3 Algorithm, Toward Enhancing Supply Chain Management in Healthcare Field," *IEEE Access*, vol. 11, no. September, pp. 125897–125908, 2023, doi: 10.1109/ACCESS.2023.3330691.
25. S. Roy and M. Mitra, "Enhancing Efficiency in Healthcare Supply Chains: Leveraging Machine Learning for Optimized Operations," *Int. J. Multidiscip. Res.*, vol. 3, p. 2, 2021, doi: 10.36948/ijfmr.2021.v03i06.10323.
26. R. JP, P. Waghodekar, V. Manimegalai, A. Kumar Singh, A. Ramesh, and S. Jackson P V, "Data-Driven Approaches to Improve Healthcare Supply Chain Management," *J. Neonatal Surg.*, vol. 14, no. 8S, pp. 814–825, Mar. 2025, doi: 10.52783/jns.v14.2609.
27. M. Hussain, M. M. Ajmal, A. Gunasekaran, and M. Khan, "Exploration of social sustainability in healthcare supply chain," *J. Clean. Prod.*, vol. 203, pp. 977–989, 2018.