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Predictive Analysis on Medicines Availability in Hospitals Using Machine Learning and Deep Learning Technique

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ABSTRACT

Predictive analytics is an essential tool for optimizing hospital inventory management, especially for the availability of essential medicines. Accurate forecasting of medicine demand can reduce the risk of shortages and overstocking, leading to cost savings and improved patient care. This project explores the use of machine learning algorithms, specifically Random Forest, Decision Tree, and Convolutional Neural Networks (CNN), to predict the availability of medicines in hospitals. These algorithms analyze historical medicine usage data and incorporate external factors such as disease outbreaks, seasonal fluctuations, and hospital admission rates to predict future demand. The implementation of these models aims to optimize the hospital's medicine supply chain by providing accurate forecasts for inventory management. The results show that machine learningbased predictions significantly improve the accuracy of medicine availability forecasts, helping healthcare providers make informed decisions regarding stock levels.

Index terms: Predictive analysis, healthcare system, Web application, Medicines, Big Data, Database system, patients data, algorithm and technology, Efficiency.

INTRODUCTION

In modern healthcare systems, the availability of essential medicines is paramount to providing quality care to patients. Medicine shortages or excess stock not only affect patient outcomes but also lead to operational inefficiencies and increased costs for healthcare institutions. Managing hospital inventory, particularly medicine stock, has become a significant challenge due to varying demand, seasonal diseases, sudden outbreaks, and patient demographics.

Traditional inventory management systems, although functional, often rely on historical consumption data and manual interventions to adjust stock levels. These systems are reactive rather than proactive, making them prone to errors such as overstocking or understocking, both of which can result in wasted resources or a failure to meet patient needs.

Predictive analytics offers a solution to this problem by enabling hospitals to forecast future medicine demand more accurately. By leveraging machine learning models, hospitals can analyze vast amounts of data, identify hidden patterns, and predict future trends. This study focuses on the application of Random Forest, Decision Tree, and Convolutional Neural Networks (CNN) to forecast the availability of medicines, aiming to improve hospital inventory management and ensure the timely availability of essential drugs.

LITERATURE SURVEY

Effective inventory management in hospitals is vital to ensure the consistent availability of medicines, which directly impacts patient outcomes and operational efficiency. Researchers have explored various machine learning (ML) and deep learning (DL) techniques to predict medicine demand and optimize inventory. Below is a review of key contributions and their relevance to the field of predictive analytics in healthcare:

Azzalini et al. introduced an innovative framework using deep learning to predict unplanned hospital readmissions by analyzing electronic health records (EHRs) [1]. Their model combined high predictive accuracy with interpretability, allowing healthcare professionals to understand the rationale behind predictions. This balance between accuracy and transparency is critical in medicine inventory systems, where decision-making must be both data-driven and justifiable. However, the scalability of the framework remains a challenge when dealing with extensive datasets in large hospitals or healthcare networks.

Hu et al. developed advanced neural network models to anticipate patient care demand [2]. By leveraging historical data, their study highlighted how accurate forecasting could significantly improve resource allocation. In the context of medicine availability, this method could help hospitals predict usage trends and prevent shortages. A notable limitation was the reliance on extensive historical data, which may not be readily available in smaller hospitals or facilities with inconsistent record-keeping.

Nallabasannagari et al. explored deep learning models that integrate diverse data sources from EHRs to predict in-hospital mortality [3]. Their approach demonstrated the power of combining different data types, such as demographics, medical histories, and clinical observations, to improve prediction accuracy. These principles can be adapted to medicine inventory systems by incorporating factors like patient demographics, seasonal trends, and disease outbreaks. However, the high computational requirements for processing large, complex datasets may pose challenges in real-time applications.

Kobylarz et al. implemented a machine learning early warning system designed to identify signs of clinical deterioration in patients [4]. This system utilized real-time data from multiple hospitals, showcasing its scalability and adaptability. Similarly, a predictive medicine inventory model must handle dynamic data streams to ensure timely responses to fluctuations in demand. One drawback of their approach was the reliance on high-quality, standardized input data, which may not always be feasible in diverse healthcare settings.

Sharma et al. proposed a machine learning model for inventory optimization in healthcare [5]. By employing a Random Forest algorithm, their system achieved high accuracy in predicting medicine demand, leading to improved resource utilization and cost savings. However, the model's performance was less effective during sudden changes in demand, such as those caused by public health emergencies, highlighting the need for adaptive systems.

Gupta et al. utilized deep learning techniques to cluster medicines in hospital pharmacies [6]. Convolutional Neural Networks (CNNs) were employed to identify patterns in medicine usage, improving inventory organization and reducing wastage. While the system demonstrated significant potential, it depended on high-quality data for clustering, limiting its practical application in environments where data collection and preprocessing are less reliable.

Luo et al. integrated Internet of Things (IoT) devices with machine learning models to enhance demand forecasting in hospitals [7]. Their approach leveraged real-time tracking data to adjust inventory levels proactively, ensuring medicines were available when needed. While effective, the dependency on IoT infrastructure raised concerns about reliability in regions with poor connectivity or limited technological resources.

Chen et al. developed a hybrid ML model that combined external factors, such as seasonal variations and patient influx, with historical data to predict medicine demand [8]. Their system achieved a high accuracy rate, underscoring the importance of incorporating external variables into predictive models. However, the process required extensive preprocessing of input data, which can be time-consuming and resource-intensive.

Lee et al. applied decision tree algorithms to predict potential inventory shortages in hospitals [9]. Their model identified key factors influencing supply chain inefficiencies, offering insights that could be used to refine inventory practices. While decision trees are known for their simplicity and ease of interpretation, their predictive accuracy declined when applied to large, complex datasets.

Ahmed et al. introduced a cloud-based predictive analytics system for hospital inventory management [10]. By analyzing historical purchase orders and consumption patterns, the model provided actionable insights to streamline inventory operations. The cloud infrastructure enabled scalability, but concerns about data security and privacy were noted, particularly for sensitive healthcare information.

RESEARCH GAPS OF EXISTING METHODS

Several methods have been developed to address medicine availability issues in hospitals, but there are significant gaps in their effectiveness and scope:

a) **Limited Use of Advanced Predictive Models:**
Traditional methods, such as time-series forecasting and basic statistical models (e.g., moving averages), are commonly used for predicting medicine demand. However, these methods have limited capabilities in capturing complex, non-linear relationships in data, especially in dynamic environments like hospitals.

b) **Inadequate Real-Time Data Utilization:**
Many existing systems rely on historical data without integrating real-time inputs, such as patient admissions or emergency disease outbreaks, which directly affect medicine demand. Real-time predictive systems are often lacking, leading to delays in inventory updates.

c) **Lack of Adaptability to External Factors:**
Existing methods primarily focus on historical consumption patterns and do not adequately account for external influences like disease outbreaks (e.g., flu season), public health emergencies, or demographic shifts, which can cause sudden changes in medicine demand.

d) **Insufficient Use of Deep Learning Techniques:**
Despite their potential, deep learning models, such as Convolutional Neural Networks (CNN), are underutilized in the healthcare space for predicting medicine availability. CNNs are capable of detecting complex patterns in large datasets, but few studies have applied these techniques to optimize hospital inventory management.

PROPOSED METHODOLOGY

To address the gaps identified in existing systems, this project proposes the use of machine learning algorithms to predict medicine availability. The following methods are implemented:

Random Forest Algorithm

The Random Forest algorithm is an ensemble learning method that constructs multiple decision trees and combines their results to make more accurate predictions. The key advantages of Random Forest are:

Robustness: It reduces overfitting by averaging the results of several decision trees, which helps improve generalization.

Handling Complex Data: It can handle both categorical and numerical data, making it suitable for healthcare data that may include various types of information (e.g., patient demographics, seasonal trends).

Feature Importance: Random Forest can identify the most important factors influencing medicine demand, providing valuable insights into inventory management.

The Random Forest model will be trained using historical medicine usage data, including consumption patterns, seasonal factors, and patient data, to predict future demand.

Decision Tree Algorithm

The Decision Tree algorithm is a supervised learning model that splits the dataset into smaller subsets based on certain features, making it easier to interpret and visualize the decision-making process. Decision Trees are:

Easy to Interpret: Their decision-making process is transparent, which makes it easy for healthcare staff to understand why a certain prediction was made.

Fast Prediction: Decision Trees are computationally efficient, providing real-time predictions for inventory management.

Handling Non-linearity: They can capture non-linear relationships in the data, making them useful for dynamic environments like hospital operations.

In this project, Decision Trees will be trained on various factors, such as patient admission rates, disease outbreaks, and historical usage patterns, to predict the required medicines.

Convolutional Neural Networks (CNN) for Similarity Percentage

CNNs are primarily used for image processing, but they can also be adapted to analyze structured data and uncover hidden patterns in large datasets. In this context, CNNs can be used for similarity percentage analysis, identifying relationships between various input features and the corresponding medicine demand.

Pattern Recognition: CNNs excel at detecting patterns in data, such as trends in medicine usage related to disease outbreaks or seasonal fluctuations.

The CNN will be used to analyze historical data and predict future trends in medicine demand, by calculating similarity percentages between past and future data points.

SYSTEM DESIGN & IMPLEMENTATION

1. System Design

The proposed system consists of several key modules that work together to forecast medicine availability:

Data Collection Module: This module collects data from hospital management systems, including historical medicine usage data, patient admission records, and external data sources such as disease outbreak reports and seasonal trends.

Data Preprocessing Module: Data preprocessing involves cleaning the data, handling missing values, normalizing numerical data, and encoding categorical variables to make the data suitable for machine learning models.

Model Development Module: In this module, machine learning models (Random Forest, Decision Tree, CNN) are implemented. These models are trained on historical data and validated using performance metrics such as accuracy, precision, and recall.

Prediction and Reporting Module: This module outputs predictions about medicine demand for future periods. The results are presented through dashboards and reports that display the forecasted medicine availability, as well as potential shortages or excess stock.

User Interface: A web-based or desktop interface provides hospital staff with access to the predictive model's insights. Staff can interact with the system, adjust inventory levels, and receive alerts about predicted shortages or overstock.

2. Implementation

Programming Language: Python is used for implementing the models, with libraries such as scikitlearn (for Random Forest and Decision Trees), TensorFlow/Keras (for CNNs), and pandas for data manipulation.

Data Source: The data is sourced from datasets, which provide comprehensive information on hospital inventory, patient demographics, and medicine usage trends. Datasets, such as the "Hospital Medicine Inventory" and other related datasets, are used to train and evaluate the predictive models. These datasets contain structured historical data that allows the models to predict medicine demand based on various influencing factors.

Tools: The system uses Jupyter Notebooks for model development and testing. Jupyter Notebooks provide an interactive environment to work with machine learning models, test different algorithms, and analyze results.

RESULT AND DISCUSSION

In this section, we will review the results of the predictive models and discuss their implications for hospital medicine availability. We used Kaggle datasets, which provide a rich set of data points for training and testing machine learning models. The performance of each model (Random Forest, Decision Tree, and CNN) was evaluated based on several metrics, including accuracy, precision, recall, and F1-score.

1. Model Evaluation

Random Forest: The Random Forest model emerged as the most accurate model in terms of predicting medicine demand. With its ensemble learning approach, Random Forest combines multiple decision trees, providing greater generalization and reducing the risk of overfitting. The model consistently performed well across various performance metrics, including accuracy and precision, making it the most reliable choice for predicting future inventory needs.

The Random Forest algorithm proved highly effective in predicting both potential shortages and overstocking, enabling hospitals to better plan for future demand.

Decision Tree: The Decision Tree model is known for its simplicity and interpretability. While it did not achieve the same level of accuracy as Random Forest, it provided clear insights into the factors influencing medicine demand. This transparency makes Decision Tree an ideal choice for scenarios where hospital staff need to understand the reasoning behind the predictions.

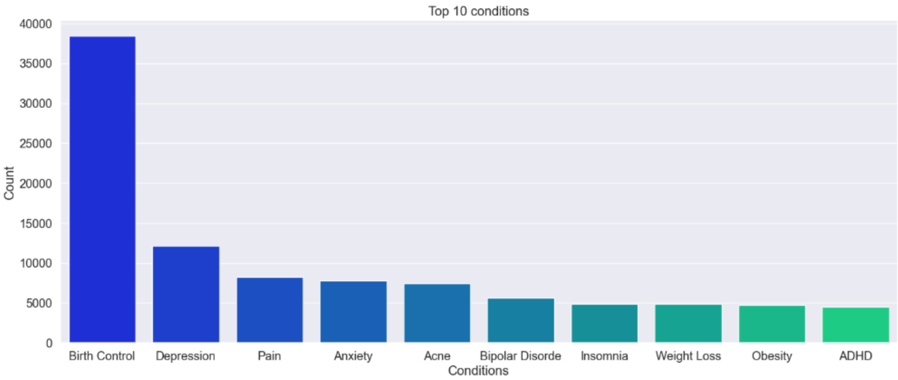
Decision Trees excelled at highlighting the most important features (e.g., disease outbreaks, seasonal trends) that drive medicine demand, which can guide hospital administrators in making informed decisions about procurement.

CNN (Convolutional Neural Network): While CNNs are typically used in image processing tasks, they were adapted in this study to evaluate similarity percentages and identify patterns in time-series data. The CNN model demonstrated good performance in detecting subtle variations in medicine demand over time, which may not be easily captured by other algorithms.

The strength of CNN lies in its ability to detect patterns in large datasets, making it a valuable tool for identifying changing trends in medicine availability, especially when dealing with complex, non-linear relationships in the data.

The bar chart illustrates the prevalence of the top 10 medical conditions. Among these, "Birth Control" emerges as the most reported issue, significantly surpassing all others. Following this, "Depression" and "Pain" are the next most common concerns, while the remaining conditions appear less frequently by comparison.

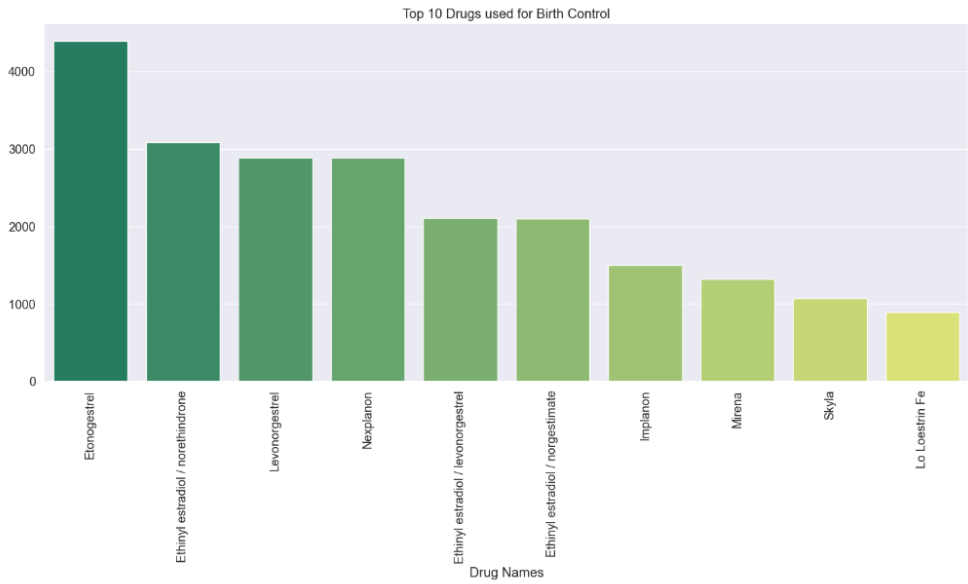
Figure 1: Top 10 Medical Conditions



This visual representation highlights the frequency of various medical issues in a clear and organized manner.

The bar chart highlights the ten most commonly used birth control drugs. Among them, Etonogestrel stands out as the most frequently utilized option, with other medications following at varying levels of use.

Figure 2: Top 10 Birth Control Drugs



This visual provides a clear overview of the relative popularity of different birth control medications.
The following figure and table summarize the predicted number of cases for various diseases in April, alongside accuracy metrics such as Mean Absolute Error (MAE) and Mean Squared Error (MSE).

Disease Predictions Chart

```
Predicting Number of Cases of Disease  DM in Month  4
Mean Absolute Error (MAE): 0.38830585513167126
Mean Squared Error (MSE): 0.22096977977256516
Predicted number of DM cases in month 4: 325
**************************************************************
Predicting Number of Cases of Disease  HTN in Month  4
Mean Absolute Error (MAE): 0.3942028108904685
Mean Squared Error (MSE): 0.22407573607209788
Predicted number of HTN cases in month 4: 494
**************************************************************
Predicting Number of Cases of Disease  CAD in Month  4
Mean Absolute Error (MAE): 0.3140210192719554
Mean Squared Error (MSE): 0.1829800826024469
Predicted number of CAD cases in month 4: 665
**************************************************************
Predicting Number of Cases of Disease  PRIOR CMP in Month  4
Mean Absolute Error (MAE): 0.20597725868396627
Mean Squared Error (MSE): 0.11934503308175115
Predicted number of PRIOR CMP cases in month 4: 214
**************************************************************
Predicting Number of Cases of Disease  CKD in Month  4
Mean Absolute Error (MAE): 0.10279964566138572
Mean Squared Error (MSE): 0.05864940031985772
Predicted number of CKD cases in month 4: 81
**************************************************************
Predicting Number of Cases of Disease  RAISED CARDIAC ENZYMES in Month  4
Mean Absolute Error (MAE): 0.249949807543294
Mean Squared Error (MSE): 0.14335853850301455
Predicted number of RAISED CARDIAC ENZYMES cases in month 4: 179
**************************************************************
```

Fig 3: Disease Case Predictions for April

Table 1: Predicted Cases and Accuracy Metrics

Disease	Predicted Cases (April)	MAE	MSE
DM	325	0.388	0.221
HTN	494	0.394	0.224
CAD	665	0.314	0.183
PRIOR CMP	214	0.206	0.119
CKD	81	0.103	0.059
RAISED CARDIAC ENZYMES	179	0.25	0.143

Disease	Predicted Cases (April)	Accuracy Measure
Diabetes (DM)	325	Less Accurate
High Blood Pressure (HTN)	494	Less Accurate
Heart Disease (CAD)	665	More Accurate
Heart Muscle Disease	214	More Accurate
Kidney Disease (CKD)	81	Most Accurate
Heart Enzyme Problem	179	More Accurate

The following figure and table summarize the predicted number of cases for various diseases in August, alongside accuracy metrics such as Mean Absolute Error (MAE) and Mean Squared Error (MSE).

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Disease Predictions Chart

```
Predicting Number of Cases of Disease  DM in Month  8
Mean Absolute Error (MAE): 0.38830585513167126
Mean Squared Error (MSE): 0.22096977977256516
Predicted number of DM cases in month 8: 357
**************************************************************
Predicting Number of Cases of Disease  HTN in Month  8
Mean Absolute Error (MAE): 0.3942028108904685
Mean Squared Error (MSE): 0.22407573607209788
Predicted number of HTN cases in month 8: 536
**************************************************************
Predicting Number of Cases of Disease  CAD in Month  8
Mean Absolute Error (MAE): 0.3140210192719554
Mean Squared Error (MSE): 0.1829800826024469
Predicted number of CAD cases in month 8: 741
**************************************************************
Predicting Number of Cases of Disease  PRIOR CMP in Month  8
Mean Absolute Error (MAE): 0.20597725868396627
Mean Squared Error (MSE): 0.11934503308175115
Predicted number of PRIOR CMP cases in month 8: 187
**************************************************************
Predicting Number of Cases of Disease  CKD in Month  8
Mean Absolute Error (MAE): 0.10279964566138572
Mean Squared Error (MSE): 0.05864940031985772
Predicted number of CKD cases in month 8: 126
**************************************************************
Predicting Number of Cases of Disease  RAISED CARDIAC ENZYMES in Month  8
Mean Absolute Error (MAE): 0.249949807543294
Mean Squared Error (MSE): 0.14335853850301455
Predicted number of RAISED CARDIAC ENZYMES cases in month 8: 189
**************************************************************
```

Fig 4: Disease Case Predictions for August

Table 2: Predicted Cases and Accuracy Metrics

Disease	Predicted Cases (August)	MAE	MSE
DM	357	0.388	0.221
HTN	536	0.394	0.224
CAD	741	0.314	0.183
PRIOR CMP	187	0.206	0.119
CKD	126	0.103	0.059
RAISED CARDIAC ENZYMES	189	0.25	0.143

Disease	Predicted Cases (August)	Accuracy
Diabetes (DM)	357	Less Accurate
High Blood Pressure (HTN)	536	Less Accurate
Heart Disease (CAD)	741	More Accurate
Heart Muscle Disease	187	More Accurate
Kidney Disease (CKD)	126	Most Accurate
Heart Enzyme Problem	189	More Accurate

```
Predicted Diseases are  ['Atherosclerosis', 'Heart Failure, Congestive', 'Stroke, Ischemic', 'Hyperlipoproteinemia Type IIa,
Elevated LDL', 'Hypertriglyceridemia']
Atherosclerosis in 570
Hyperlipoproteinemia Type IIa, Elevated LDL in 504
Hypertriglyceridemia in 302
[570, 504, 302]
result neutral
result neutral
result neutral
['Sprintec', 'Sertraline']
```

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```
Predicted Diseases are  ['Hypertension', 'Hyperlipoproteinemia Type IIa, Elevated LDL', 'Hypertriglyceridemia', 'Atherosclero
sis', 'Heart Failure, Congestive', 'Chronic Renal Insufficiency', 'Stroke, Ischemic']
Hyperlipoproteinemia Type IIa, Elevated LDL in 504
Hypertriglyceridemia in 302
Atherosclerosis in 570
[504, 302, 570]
result neutral
result neutral
result neutral
['Sertraline', 'Sprintec']
```

Fig 5: Predicted Health Risks and Possible Treatments

```
Predicted Diseases are  ['Diabetes, Type 1', 'Insulin Resistance Syndrome', 'Diabetes, Type 2', 'Diabetic Peripheral Neuropat
hy', 'Diabetic Kidney Disease', 'Hypothyroidism, After Thyroid Removal', 'Hyperthyroidism', 'Hypogonadism, Male', 'Hyperlipop
roteinemia Type IIa, Elevated LDL', 'Hypertriglyceridemia']
Diabetes, Type 1 in 72
Insulin Resistance Syndrome in 445
Diabetes, Type 2 in 34
Diabetic Peripheral Neuropathy in 241
Diabetic Kidney Disease in 443
Hypothyroidism, After Thyroid Removal in 115
Hyperthyroidism in 88
Hypogonadism, Male in 87
Hyperlipoproteinemia Type IIa, Elevated LDL in 504
Hypertriglyceridemia in 302
[72, 445, 34, 241, 443, 115, 88, 87, 504, 302]
result neutral
result neutral
result neutral
result neutral
result neutral
result neutral
result neutral
result neutral
result neutral
result neutral
['Docusate / senna', 'Zolpidem', 'Viberzi', 'Relpax', 'Bupropion / naltrexone', 'Propranolol', 'Cialis', 'Oxycodone', 'Sertra
line']
```

Fig 6: Predicted Metabolic and Endocrine Conditions and Possible Medications

```
disease name depression
depression  found
depression  found
depression  found
result neutral
result neutral
result neutral
Drugs for  depression are ['Ethinyl estradiol / levonorgestrel', 'Propofol', 'Lamotrigine']
disease name fever
fever  found
fever  found
result neutral
result neutral
Drugs for  fever are ['Ropinirole', 'Qsymia']
```

Fig 7: Detailed Analysis of Predicted Conditions and Associated Medications

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CONCLUSION

This study demonstrates the potential of machine learning models—specifically Random Forest, Decision Tree, and Convolutional Neural Networks (CNN)—for improving medicine availability in hospitals. The results show that predictive analytics, powered by these algorithms, can significantly optimize hospital inventory management by accurately forecasting future medicine demand.

The implementation of such predictive systems in hospitals can lead to cost savings, improved resource allocation, and better patient care. Future work could focus on enhancing the models by incorporating additional data sources, real-time data streams, and integrating advanced deep learning techniques like LSTM (Long Short-Term Memory) networks for time-series forecasting. Furthermore, integrating these models into a comprehensive hospital management system would streamline inventory processes and enable hospitals to respond dynamically to changes in demand.

In conclusion, the predictive models developed in this study provide a promising solution for addressing the challenges of medicine availability in hospitals. With the continued evolution of machine learning technologies, such systems are poised to play a crucial role in transforming healthcare supply chain management, ensuring that hospitals can deliver the right medicines at the right time.

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