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Optimizing Pharmaceutical Inventory Control: Strategies for Classification and Seasonal Demand Forecasting

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Abstract: Effective pharmaceutical inventory management is critical for assuring the availability of necessary pharmaceuticals, avoiding the waste, and managing the costs in healthcare systems. The complexities of pharmaceutical inventory management are worsened by factors such as varied degrees of criticality, unexpected demand patterns, short shelf life, and resource constraint. This study looks at major inventory management frameworks including ABC, VED, and SDE analyses, which classify drugs based on their value, criticality, and supply risks, allowing for more accurate inventory calculations. Furthermore, the study emphasizes the use of machine learning models and time series forecasting approaches, notably SARIMA and LSTM, to predict seasonal demand fluctuations and improve inventory planning and decision-making processes.

Although much research has been undertaken on the deployment of these approaches in a variety of industries, there is a significant gap in their application to pharmaceutical inventory management, particularly in resource-constrained contexts with insufficient historical data. This work seeks to close this gap by investigating how time series models might be modified to estimate demand seasonality in the absence of comprehensive historical data. The findings highlight the ability of SARIMA and LSTM to increase the forecasting accuracy and guide superior inventory managing methods, resulting in more efficient supply chains management and better decision-making in pharmaceutical contexts. The major goal is to use time series models to address seasonality difficulties in pharmaceutical inventory management, especially when data availability is limited.

Keywords: *ABC Analysis, VED Analysis, SDE Analysis, Seasonal Demand Prediction, Inventory Optimization, ARIMA, SARIMA, LSTM.*

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I. INTRODUCTION

Pharmaceutical inventory management plays a crucial role in healthcare systems by ensuring the continuous availability of essential medications while minimizing waste and controlling costs. Effective inventory management in pharmacies and healthcare facilities directly impacts patient care, operational efficiency, and financial sustainability. Proper handling of pharmaceutical inventories is vital to maintaining adequate stock levels, streamlining supply chains, and addressing the risks of drug shortages or surplus inventory. Inefficient management in this area can lead to serious consequences, such as treatment delays, higher healthcare costs, and negative health outcomes.

Despite its importance, managing pharmaceutical inventories presents unique challenges. The wide variety of pharmaceutical products, each with distinct demand patterns, shelf lives, and criticality levels, makes the process complex. Additionally, demand variations caused by factors like seasonality, outbreaks, and shifting health trends further complicate accurate forecasting. The varying criticality of medications, ranging from life-saving drugs to less critical ones, requires tailored inventory strategies that balance cost efficiency with service quality.

This study aims to explore methods for improving inventory management in pharmacy systems by identifying critical parameters such as reorder quantities, safety stock levels, and reorder points. Special attention is given to

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classification-based frameworks like ABC (Always Better Control), VED (Vital, Essential, Desirable), and SDE (Scarce, Difficult to Obtain, Easily Available) analyses. These methodologies help categorize inventory items based on their value, criticality, and availability, enabling pharmacies to implement systematic inventory management practices that optimize stock availability while maintaining cost-effectiveness.

Unlike traditional studies that rely on sample datasets, this review focuses on applying ABC, VED, and SDE analyses in real-world pharmacy settings, where obtaining precise data can be challenging. These approaches provide flexible frameworks suitable for both large healthcare institutions and smaller pharmacies with limited resources. The review also highlights the impact of seasonal demand variations, recognizing the need for dynamic inventory adjustments during peak seasons or health crises to ensure optimal performance and medication availability.

II. CLASSIFICATION-BASED FRAMEWORKS IN INVENTORY CONTROL

Effective inventory control is essential for efficient supply chain management, especially in the healthcare and pharmaceutical sectors, where stock shortages or excess inventory can disrupt operations and compromise patient care. One widely adopted approach for optimizing inventory management is the use of classification-based frameworks, which organize inventory items systematically based on criteria like value, criticality, or supply variability, facilitating better prioritization and resource allocation.

Classification-based methodologies, such as ABC (Activity-Based Costing) analysis, VED (Vital, Essential, Desirable) analysis, and SDE (Scarce, Difficult to Obtain, Easily Available) analysis, offer structured strategies to enhance inventory control. Each framework targets specific aspects of inventory management, ensuring that resources are utilized effectively to address the most pressing needs.

A. ABC Analysis

ABC analysis is a classification technique that organizes inventory items based on their value or consumption rate. It divides items into three categories: A (high-value items), B (moderate-value items), and C (low-value items). This method is widely applied in pharmaceutical inventory management to prioritize stock according to its economic significance.

Research by Bialas et al. (2023) emphasized the critical role of ABC analysis in hospital pharmacies, where managing high-value medications effectively is crucial for streamlining procurement processes and reducing overall costs. Similarly, Nasution et al. (2024) highlighted how this approach enables healthcare providers to allocate resources more effectively by focusing on high-cost, high-use items during procurement planning.

Gizaw and Jemal (2023) expanded the application of ABC analysis by integrating it with VED (Vital, Essential, Desirable) analysis to refine classifications based on clinical importance. Their study revealed that many high-value (Category A) items are also critical for patient care, enhancing procurement decisions and inventory control. Likewise, Benny Alexandri et al. (2023) explored the use of ABC analysis in relation to cost and usage value, underscoring the need to closely monitor high-investment drugs to prevent shortages and mitigate financial risks.

By combining ABC analysis with other methodologies, healthcare institutions can improve procurement strategies, minimize waste, and avoid overstocking. This approach not only prioritizes essential and high-cost items but also helps reduce the operational costs associated with excess inventory of low-value items (Jadhav & Khandelwal, 2024). These findings demonstrate the importance of ABC analysis in optimizing inventory management practices and enhancing the efficiency of healthcare services.

Table 1: ABC Analysis Categories and Management Approach

Category	Criteria	Focus
A	High annual consumption value	Close monitoring and tight inventory control.
B	Moderate annual consumption value	Periodic review and balanced stock management.
C	Low annual consumption value	Minimal monitoring and simplified management.

B. VED Analysis

VED analysis is a framework that assesses the criticality of pharmaceutical items, categorizing them into three groups: Vital (V), Essential (E), and Desirable (D). Vital items are indispensable for life-saving treatments, essential items are significant but not critical, and desirable items are assigned a lower priority. Bialas et al. (2023) posited "that VED analysis is vital for ensuring the continuous availability of critical medications". Their research emphasized the necessity of clinical input in determining the criticality levels of medications, which has direct implications for procurement and inventory management.

Gizaw and Jemal (2023) also integrated VED analysis with ABC classification, asserting that drugs classified as vital were automatically designated as A items, irrespective of their consumption value. This methodology facilitated the prioritization of vital medications, ensuring that essential supplies were not neglected. Additionally, Umadevi and Umamaheswari (2023) employed a combined ABC-VED matrix for pharmaceutical inventory management, ensuring that both economic value and clinical importance were taken into account in stock prioritization. This dual approach enhances inventory efficiency by addressing both cost considerations and patient care requirements.

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The integration of VED with ABC or SDE analysis offers a comprehensive strategy for managing pharmaceutical inventory. While ABC emphasizes value and usage, VED focuses on the criticality of items, rendering the amalgamation of these methodologies particularly advantageous in healthcare settings where patient safety is paramount (Kishore & Reddy, 2023).

Table 2: VED Analysis Categories and Purpose

Category	Criteria	Purpose
Vital (V)	Critical for operations or survival	Always ensure availability at all times.
Essential (E)	Important but not critical	Maintain consistent supply without overstock.
Desirable (D)	Not immediately critical; can be deferred	Stock based on budget and demand patterns.

C. SDE Analysis

SDE analysis emphasizes the supply chain dimension of inventory management by categorizing items into three classifications: Scarce (S), Difficult (D), and Easily Available (E). This analytical approach is essential for managing items that are challenging to procure or are influenced by fluctuations in the supply chain. Setyadi et al. (2024) elucidated how SDE analysis facilitates the identification of drugs that are difficult to acquire, thereby enabling more strategic procurement practices and enhanced risk management. By classifying items according to their supply reliability, pharmacies can modify their ordering strategies to reduce stockouts and ensure the availability of critical medications.

In the work of Nasution et al. (2024), "the integration of SDE analysis with Reorder Point (ROP) and Safety Stock (SS) methodologies was illustrated as a means to more effectively manage items that are scarce or difficult to procure". This integration ensures that pharmacies can sustain appropriate stock levels despite uncertainties in the supply chain. Additionally, Gizaw and Jemal (2023) incorporated SDE analysis into their ABC-VED-FNS matrix, thereby further optimizing inventory management by addressing both the criticality of items and the variability in supply within the pharmaceutical supply chain.

Table 3: SDE Analysis Categories and Procurement Strategy

Category	Criteria	Management Approach
Scarce (S)	Hard to procure due to limited availability	Advance planning and alternate sourcing.
Difficult (D)	Challenging but not impossible to obtain	Strategic procurement and buffer stock.
Easy (E)	Readily available with minimal issues	Routine procurement and low buffer needs.

The combined use of ABC, VED, and SDE analyses provides a robust framework for improving inventory control by addressing key aspects such as cost, availability, and demand variability. ABC analysis focuses on categorizing inventory based on value, allowing organizations to prioritize high-value items (Category A) and allocate resources effectively to ensure their availability. This approach helps minimize costs while avoiding stockouts of critical products. In contrast, VED analysis emphasizes the criticality of items by classifying them into Vital, Essential, and Desirable categories. This ensures that vital items, which are essential for operations, receive priority during procurement and inventory planning. SDE analysis complements these methods by categorizing items based on supply and demand variability, with a focus on securing items that are scarce or have unpredictable demand, thereby reducing the risk of shortages.

The integration of these three frameworks enables a more comprehensive and strategic approach to inventory management. By combining insights from ABC, VED, and SDE, organizations can make well-informed decisions regarding procurement, stock levels, and reorder points. This integration ensures that cost efficiency, criticality, and supply variability are all considered, leading to better resource allocation and improved inventory turnover. Incorporating seasonal demand patterns into the SDE framework further enhances forecasting and planning, preventing overstocking during low-demand periods and ensuring adequate supplies during peak seasons.

Together, these methodologies optimize stock levels, reduce waste, and enhance the efficiency of inventory management systems. By balancing cost control, operational needs, and supply chain dynamics, organizations can improve responsiveness, minimize risks, and achieve greater overall effectiveness in inventory management.

Table 4: Overview of ABC, VED, and SDE Analysis

Analysis Type	Classification Criteria	Purpose
ABC Analysis	Based on annual consumption value	Helps focus inventory control efforts by dividing items into three groups (A, B, and C) based on their contribution to overall expenditure.
VED Analysis	Based on criticality to operations	Ensures critical supplies remain available by classifying items as Vital, Essential, or Desirable.
SDE Analysis	Based on supply risk or ease of procurement	Facilitates procurement planning by identifying items as Scarce, Difficult, or Easy to obtain.

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III. KEY FORMULAS FOR PHARMACEUTICAL INVENTORY MANAGEMENT

Efficient pharmaceutical inventory management requires a thorough understanding of key formulas that help determine optimal stock levels, ordering schedules, and safety measures. Mathematical models such as Economic Order Quantity (EOQ), Safety Stock (SS), Reorder Point (ROP), and Demand Calculation form the basis of effective inventory control. These models help strike a balance between preventing stockouts and avoiding overstocking, which can lead to waste or product expiration. By leveraging these formulas, organizations can streamline inventory management, ensuring a consistent supply of essential medications while controlling costs. The following section explores these critical formulas and their applications in pharmaceutical inventory systems.

A. *Demand (D)*

Demand is a vital factor in calculating order quantities and ensuring the supply chain meets future requirements. It is typically expressed as the number of units required over a specific period, such as daily, weekly, monthly, or yearly, depending on the operational cycle. Accurate demand forecasting is essential for maintaining appropriate stock levels, enabling pharmaceutical companies to meet customer needs efficiently while avoiding excess inventory.

$$D = \frac{\text{Total units used during a period}}{\text{Time Period}}$$

Where:

- D is the demand (number of units required per period).

The study "Implementation of Economic Order Quantity and Reorder Point Methods in Inventory Management Information Systems" by Setyadi et al. (2021) highlights the importance of accurate demand forecasting in establishing suitable inventory levels. This process helps businesses better predict future needs and plan inventory replenishment efficiently.

B. *Economic Order Quantity (EOQ)*

The Economic Order Quantity (EOQ) model is a fundamental tool in inventory management, designed to calculate the optimal order quantity that minimizes total inventory costs, including both ordering and holding costs. By determining the most cost-effective quantity for each order, the EOQ model helps reduce overall inventory management expenses. The formula for EOQ is as follows:

$$\text{EOQ} = \sqrt{\frac{DS}{H}}$$

Where:

- D is the demand (units per year),
- S is the ordering cost per order,
- H is the holding cost per unit per year.

The EOQ model is widely applied in pharmaceutical inventory systems to maintain balanced stock levels. As highlighted by Alexandri et al. (2022), this approach is particularly useful in determining the optimal quantity of medications to order, effectively balancing the costs of ordering and holding inventory. In pharmaceutical contexts, the EOQ model has been proven to support optimal drug inventory levels while reducing unnecessary costs.

C. *Safety Stock (SS)*

Safety stock is the extra inventory maintained as a buffer to prevent stockouts caused by unexpected increases in demand or delays in the supply chain. This additional stock ensures that essential pharmaceuticals remain available even during supply disruptions or demand surges. The formula for calculating safety stock is:

$$SS = Z \times \sigma \times \sqrt{L}$$

Where:

- SS is the safety stock,
- Z is the safety factor (depends on desired service level),
- σ is the standard deviation of demand during the lead time,
- L is the lead time in days.

Nasution et al. (2020) emphasized the importance of implementing safety stock in pharmaceutical inventory management to address demand variability and supply chain delays. Maintaining safety stock ensures that sufficient inventory is available to meet demand while awaiting new orders, helping to avoid shortages of critical medications.

D. *Reorder Point (ROP)*

The Reorder Point (ROP) is the inventory level at which a new order must be placed to replenish stock before it runs out. This calculation is based on the expected demand during the lead time and incorporates safety stock to account for unforeseen fluctuations. The formula for ROP is:

$$ROP = d \times L + SS$$

Where:

- ROP is the reorder point,
- d is the average demand per day,
- L is the lead time in days,
- SS is the safety stock.

Studies by Setyadi et al. (2021) and Lubis et al. (2021) highlight the importance of accurately determining the reorder point to prevent stockouts. This formula enables timely restocking of pharmaceutical inventory, ensuring seamless operations, avoiding shortages, and maintaining efficient supply chains.

Effective pharmaceutical inventory management relies on the integration of mathematical models to balance supply and demand efficiently. Formulas such as Demand Calculation, Economic Order Quantity (EOQ), Safety Stock (SS), and Reorder Point (ROP) are vital for optimizing inventory levels, meeting customer needs, and controlling costs.

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These models work collectively to prevent stockouts, minimize holding expenses, and streamline the replenishment process. By applying these methodologies, pharmaceutical systems can ensure the continuous availability of critical medications while improving operational efficiency and reducing waste. Research and practical applications demonstrate the value of these models in managing complex inventory demands and supporting cost-effective healthcare delivery.

IV. SEASONALITY FACTOR

Seasonality plays a critical role in shaping demand patterns for various healthcare services and products, including smoking cessation therapies and essential medications. According to research by Veldhuizen et al. (2023), smoking behaviors exhibit notable seasonal fluctuations, with increased demand for nicotine replacement therapies during winter months and higher smoking prevalence in summer. Additionally, participation in smoking cessation programs peaks between January and April, while abstinence rates are higher among individuals enrolling later in the year. These seasonal trends underline the importance of incorporating demand fluctuations into healthcare planning to optimize resource allocation, prevent underutilization during low-demand periods, and avoid overwhelming capacities during peak seasons. Anticipating these patterns enables healthcare providers to promote programs more effectively, allocate resources strategically, and improve patient outcomes through seasonally tailored interventions.

Similarly, seasonal demand has a profound impact on the availability of critical pharmaceuticals. As Shukar et al. (2023) point out, seasonal surges—driven by factors such as predictable illnesses and unpredictable epidemics—can exacerbate drug shortages. Many healthcare systems rely on just-in-time inventory models, which, while cost-efficient, are vulnerable to seasonal spikes in demand. This issue is especially pronounced in low- and middle-income countries, where additional challenges such as medication wastage and nonadherence to prescriptions intensify resource constraints.

Addressing the challenges posed by seasonal demand fluctuations requires robust forecasting systems and proactive inventory management strategies. Advanced data analytics can predict seasonal trends, enabling healthcare providers to adjust operations and mitigate shortages effectively. Policies should focus on enhancing adherence to prescriptions, minimizing wastage, and promoting stakeholder education. By factoring seasonality into healthcare and inventory planning, organizations can maintain continuity of care, reduce shortages, and safeguard patient safety during periods of heightened demand.

V. FORECASTING MODELS FOR SEASONALITY

Accurate demand forecasting is pivotal in the pharmaceutical industry, where it directly impacts inventory control, operational performance, and customer satisfaction. Seasonal variations, driven by factors such as weather changes, public holidays, and disease outbreaks, create additional complexities that necessitate specialized forecasting approaches. To address these challenges, various models ranging from classical statistical methods like ARIMA and SARIMA to advanced machine learning techniques like Long Short-Term Memory (LSTM) networks have been utilized. Below is an analysis of these models, emphasizing their applicability to the pharmaceutical context and their ability to handle seasonal demand fluctuations.

A. Models

➢ *ARIMA*

The ARIMA model is a traditional statistical tool designed for time series forecasting. It predicts future values by analyzing relationships in historical data. This model has found applications in short-term demand forecasting within the pharmaceutical sector, as demonstrated by Siddiqui et al. (2024) in their hybrid ARHOW approach. ARIMA is particularly effective at identifying dependencies in time series data over shorter periods. Some of its strengths are simplicity and computational efficiency, which make it accessible for smaller datasets and suitable for short-term predictions where demand exhibits linear trends.

It also has weaknesses it struggles to accurately forecast seasonal variations or non-linear trends, requires stationarity, necessitating significant preprocessing steps, and has limited effectiveness for data with high variability or irregular patterns. Due to these limitations, ARIMA is often integrated into hybrid forecasting models to enhance its accuracy for scenarios involving complex demand dynamics.

➢ *SARIMA*

SARIMA extends the ARIMA model by incorporating seasonal components, which allows it to effectively capture and model cyclical patterns that are often present in time series data, making it particularly valuable for industries such as pharmaceuticals where seasonal demand variations are common. For instance, SARIMA has been shown to perform well in forecasting medication sales, as highlighted by Sirishta et al. (2024), demonstrating its ability to accurately identify seasonal peaks and troughs in demand. One of SARIMA's main strengths is its capacity to handle data with defined and predictable seasonal variations, making it a suitable tool for industries that experience regular cycles in demand. However, the model does have limitations. First, it requires the data to be stationary, which can present challenges in preprocessing, particularly if the data exhibits trends or non-stationary behavior. Additionally, while SARIMA excels at modeling linear relationships, it struggles with capturing non-linear patterns in the data, making it less effective for more complex demand scenarios. Moreover, the inclusion of additional seasonal parameters increases the computational complexity, making SARIMA more resource-intensive compared to simpler models like ARIMA. Despite its strengths in seasonal demand forecasting, SARIMA is less adaptable to irregular or non-linear demand fluctuations, which can limit its effectiveness in dynamic, unpredictable environments.

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➢ *LSTM (Long Short Term Memory)*

LSTM networks, a type of recurrent neural network (RNN), are engineered to capture and forecast time series data with complex, non-linear correlations and long-term dependencies. This characteristic sets LSTM apart from traditional models like ARIMA and SARIMA, which struggle to model such complexities effectively. LSTM networks excel in handling intricate, noisy patterns over extended periods, making them particularly valuable in industries like pharmaceuticals, where demand can be irregular and subject to various seasonal variations. According to research by Dubey et al. (2024), LSTM outperformed both ARIMA and SARIMA in forecasting energy consumption, a task that involves complex, non-linear relationships. Similarly, Ensafia et al. (2024) found LSTM to be more effective than SARIMA in predicting retail sales, especially when dealing with large datasets that exhibit erratic trends. One of the primary strengths of LSTM is its ability to model non-linear relationships and capture long-term dependencies in time series data, making it highly effective for forecasting demand in sectors where traditional models may fall short. Additionally, LSTM requires minimal data preprocessing compared to ARIMA or SARIMA, which often necessitate transformations to make the data stationary. However, LSTM is not without its drawbacks. It is computationally intensive and requires significant time and resources for training, particularly when working with large datasets. Furthermore, the performance of LSTM is highly dependent on the availability of sufficient data; smaller datasets may not yield the same level of accuracy. Additionally, tuning the hyperparameters of LSTM can be challenging and time-consuming, requiring careful attention to optimize performance. Despite these challenges, the ability of LSTM to model complex patterns and long-term dependencies makes it a powerful tool for pharmaceutical demand forecasting, especially for products with irregular or unpredictable seasonal demand.

Table 5: Strengths and Limitations of *Models discussed*

Model	Strengths	Limitations
ARIMA	Straightforward and well-suited for data with stable patterns and linear trends	Struggles with non-linear patterns and seasonality
SARIMA	Effective for capturing seasonal patterns in data	Requires stationarity, limited to linear trends
LSTM	Excels at learning long-range dependencies and complex, nonlinear dynamics in data	Requires large datasets, computationally expensive

Table 6: Comparison of ARIMA, SARIMA, and LSTM Performance Across Various Use Cases

Paper	Use Case	ARIMA	SARIMA	LSTM
J. Liu et al. (2023)	Stock Market Prediction	- RMSE: 2.34- Accuracy: Moderate	- RMSE: 1.98- Better accuracy	- RMSE: 1.12- Best accuracy- Handles non-linearity
P. Smith et al. (2023)	Weather Forecasting	MAE: 0.56- MAPE: 5.2%	MAE: 0.45- MAPE: 3.1%	MAE: 0.31- MAPE: 2.3%- Best accuracy
R. Zhang et al. (2023)	Supply Chain Demand	RMSE: 4.21- Accuracy: 89.3%	N/A	RMSE: 2.87- Accuracy: 95.2%
M. Belavagi et al. (2022)	Profit Prediction	Accuracy: 93.84%- RMSE: 8.68	Accuracy: 94.38%- RMSE: 7.27	Accuracy: 97.01%- RMSE: 3.91
D. Wijesena et al. (2023)	Transformer Load Forecast	MAPE (%): 2.93- RMSE: 3.39	MAPE (%): 2.86- RMSE: 3.32	MAPE (%): 1.5- RMSE: 2.12- Best accuracy
A. K. Dubey et al. (2021)	Energy Consumption Forecast	MAPE (%): 19.8- MAE: 1.58 GWh	MAPE (%): 17.6- MAE: 2.08 GWh	MAPE (%): 12.1- MAE: 0.23 GWh- Best performance

B. Discussion

➢ *Accuracy and Performance*

Numerous studies have shown that Long Short-Term Memory (LSTM) networks generally outperform both Autoregressive Integrated Moving Average (ARIMA) and Seasonal ARIMA (SARIMA) in terms of predictive accuracy, especially when the data exhibit non-linear dependencies or complex patterns. This performance gap arises from the inherent strengths of LSTM networks, which are tailored to handle intricate relationships and long-term dependencies in time series data, unlike ARIMA and SARIMA, which are limited by their reliance on linear relationships and predefined lag structures.

LSTM networks excel at capturing complex, non-linear relationships, which is especially useful in forecasting tasks involving variables with intricate interdependencies. Unlike ARIMA and SARIMA, which often require explicit feature engineering, LSTM can autonomously detect and model these patterns. This makes LSTM particularly advantageous in contexts where data behavior cannot be easily described by linear trends. For example, in transformer load forecasting, LSTM outperformed SARIMA, achieving lower Mean Absolute Percentage Error (MAPE) and Mean Absolute Error (MAE), likely due to its ability to recognize deeper temporal relationships (Wijesena et al., 2023). Similarly, LSTM proved to be highly accurate in energy consumption forecasting, with a Mean Absolute Error (MAE) of 0.23, significantly

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outperforming both ARIMA and SARIMA in accuracy (Dubey et al., 2021). The flexibility of LSTM in capturing both short-term fluctuations and long-term dependencies enabled it to outperform ARIMA and SARIMA, which are primarily limited to identifying linear trends or periodic patterns.

While SARIMA, an extension of ARIMA designed to capture seasonal components, performed well when applied to datasets exhibiting clear seasonal patterns, its usefulness is confined to situations where the data follows periodic behaviors. For instance, SARIMA demonstrated strong performance in transformer load forecasting for data with discernible seasonal patterns, but it struggled with non-linear relationships or more complex data structures (Wijesena et al., 2023). Therefore, while SARIMA is a robust model for cyclical demand forecasting, it cannot effectively capture the non-linear dynamics that LSTM is capable of.

ARIMA, being a simpler model, is suitable for forecasting stationary and linear time series data. It performs well when the data does not exhibit complex seasonal patterns or long-term dependencies. However, its predictive performance diminishes when faced with non-linear relationships or long-term dependencies in the data, making it less effective than LSTM in more intricate forecasting tasks (Kumar et al., 2021). As a result, ARIMA struggles to match LSTM's accuracy, particularly in datasets with complex, non-linear dynamics.

➢ *Computational Efficiency*

Long Short-Term Memory (LSTM) networks are known for their excellent predictive accuracy, but they come with significant computational challenges. The training process for an LSTM requires backpropagation through time, which can be particularly demanding when working with large datasets or a high number of training epochs. This results in LSTM models requiring considerable computational resources, both in terms of memory and processing power, making them less efficient compared to traditional models like Autoregressive Integrated Moving Average (ARIMA) and Seasonal ARIMA (SARIMA), which are generally more lightweight and faster to train. Additionally, LSTM models require hyperparameter tuning and cross-validation to reduce the risk of overfitting, further increasing the time complexity associated with their use (Wijesena et al., 2023).

On the other hand, ARIMA is highly efficient in terms of both implementation and computation. It only requires the estimation of a few parameters, such as the number of lags (p, q) and the differencing steps (d), and does not involve extensive training periods. This makes ARIMA an excellent choice for real-time forecasting applications where computational efficiency and speed are crucial, especially in situations with limited resources (Belavagi & Attigeri, 2022). ARIMA's simpler structure and lack of iterative optimization, unlike LSTM, also make it easier to implement, even for users with limited computational expertise.

SARIMA, while more computationally intensive than ARIMA due to its inclusion of seasonal components, is generally still more efficient than LSTM for many forecasting tasks. SARIMA is suitable for data exhibiting clear seasonal patterns, as it efficiently computes seasonal lags. However, when dealing with more complex seasonality or applications requiring frequent real-time updates, the computational demands of tuning multiple seasonal parameters (P, D, Q, s) can become challenging (Wijesena et al., 2023).

In summary, while LSTM offers higher accuracy, it is the least efficient model in terms of computational resources, particularly when handling large datasets or extended training epochs. This makes LSTM less practical for real-time forecasting or applications with limited computational resources. For tasks that do not require the highest levels of accuracy or involve large datasets, traditional models like ARIMA and SARIMA are more suitable due to their relatively lower computational burden (Dubey et al., 2021).

➢ *Applicability of Forecasting Models*

The suitability of different forecasting models depends on the specific characteristics of the time series data and the forecasting objectives. Each model has distinct strengths, shaped by its ability to handle various data types and forecast horizons.

The ARIMA model is best suited for linear, stationary time series data that do not exhibit significant trends or seasonality. It performs well in situations where the relationships among observations are relatively simple and can be represented using lagged values and moving averages. For example, ARIMA is effective when forecasting time series with a consistent trend but no seasonal patterns. However, its performance declines when tasked with modeling long-term dependencies or non-linear relationships between variables.

SARIMA, an extension of ARIMA, is designed to handle data with seasonal patterns. It is particularly valuable in domains such as energy consumption forecasting, retail sales, and traffic predictions, where clear seasonal fluctuations are present. By incorporating seasonal components, SARIMA captures recurring cycles (e.g., daily, weekly, or annual), making it well-suited for datasets with predictable seasonal trends. However, its ability to model non-linear dependencies and long-term interactions is limited, which can reduce its effectiveness in more complex forecasting tasks.

Long Short-Term Memory (LSTM) networks are the most versatile for handling time series data with complex, non-linear relationships and long-term dependencies. LSTM is particularly advantageous in cases where traditional methods like ARIMA and SARIMA struggle to capture intricate patterns and interactions between variables. For example, LSTM is well-suited for tasks such as financial forecasting, profit prediction, and long-term load forecasting, where relationships between observations evolve and exhibit non-linear characteristics. LSTM's strength lies in its ability to process large datasets and model temporal dependencies, making it the preferred model when accuracy is crucial and ample computational resources are available.

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VI. CONCLUSION

Effective inventory management requires a comprehensive approach that combines inventory classification with advanced forecasting methods to maintain optimal stock levels. Techniques like ABC, VED, and SDE categorization are essential for identifying key items, enabling organizations to allocate resources effectively and avoid issues related to overstocking or stockouts. By utilizing analytical tools such as Economic Order Quantity (EOQ) and Reorder Points (ROP), businesses can align their ordering practices with demand trends, ensuring cost-efficient inventory control. This strategy guarantees the availability of crucial items while minimizing storage costs and preventing supply chain disruptions.

Accurate forecasting of seasonal demand plays a critical role, and time series models such as SARIMA and LSTM offer unique advantages for this purpose. SARIMA is particularly effective in modeling both trends and seasonality, making it suitable for datasets with regular and predictable seasonal fluctuations, such as those associated with holidays or seasonal promotions. It captures these patterns well, delivering dependable forecasts for such conditions. On the other hand, LSTM, a deep learning model, excels at identifying complex, non-linear relationships and long-term dependencies in data, making it ideal for forecasting irregular or intricate seasonal trends that do not follow consistent patterns. While LSTM outperforms SARIMA in terms of accuracy for complex data, it requires more computational resources, which can make it less efficient for simpler seasonal data. Therefore, SARIMA remains a strong choice for more predictable seasonal trends, while LSTM is better suited for handling complicated, non-linear fluctuations, especially when accuracy is paramount and computational resources are available.

By combining inventory categorization with advanced time series forecasting, businesses can improve the precision and efficiency of their inventory management processes. This holistic approach ensures the consistent availability of critical items, optimizes resource allocation, and enables proactive stock management. Ultimately, this synergy between techniques allows companies to better navigate market fluctuations, improve operational performance, and reduce the risks associated with inventory imbalances, leading to a more efficient and cost-effective supply chain.

REFERENCES

[1]. Vivek A. Deshpande, "Optimal Inventory Control Using ABC, VED & SDE Analysis for Indian Industries," National Conference on Emerging Trends in Mechanical Engineering (ETME-2008), G H Patel College of Engineering & Technology, Vallabh Vidyanagar, Gujarat, 28-29 March, 2008, Page no. 12.

[2]. Shaju George, Safaa Elrashid, "Inventory Management and Pharmaceutical Supply Chain Performance of Hospital Pharmacies in Bahrain: A Structural Equation Modeling Approach," SAGE Open, January-March 2023: 1–13, DOI: 10.1177/21582440221149717.

[3]. Amir Hossein Nobil, Amir Hosein Afshar Sedigh, Leopoldo Eduardo Cárdenas-Barrón, "Reorder point for the EOQ inventory model with imperfect quality items," Ain Shams Engineering Journal, vol. 11, issue 4, 2020, pp. 1339-1343, DOI: https://doi.org/10.1016/j.asej.2020.03.004.

[4]. Heribertus Ary Setyadi, Budi Al Amin, Pudji Widodo, "Implementation Economic Order Quantity and Reorder Point Methods in Inventory Management Information Systems," Journal of Information Systems and Informatics, vol. 6, no. 1, March 2024, DOI: 10.51519/journalisi.v6i1.647.

[5]. G. Umadevi, S. Umamaheswari, "Advancing Healthcare Service Efficacy by Optimizing Pharmaceutical Inventory Management: Leveraging ABC, VED Analysis for Trend Demand," International Journal of Statistics in Medical Research, 2023, vol. 12, pp. 283-293.

[6]. Raheel Siddiqui, Muhammad Azmat, Shehzad Ahmed, Sebastian Kummer, "A hybrid demand forecasting model for greater forecasting accuracy: the case of the pharmaceutical industry," Supply Chain Forum: An International Journal, 2022, DOI: 10.1080/16258312.2022.2030897.

[7]. Christos Bialas, Ph.D., Andreas Revanoglou, Vicky Manthou, "Improving hospital pharmacy inventory management using data segmentation," American Journal of Health-System Pharmacists, 2019, DOI: 10.1093/ajhp/zxz26.

[8]. Inayah, M. Benny Alexandri, Meita Pragiwani, "Economic Order Quantity (EOQ) Method Analysis, ABC Classification and Vital, Essential and Non-Essential (VEN) Analysis of Medicines (Case Study at Pharmacy Clinic Dharma Tangerang)," IJBAM, vol. 5, no. 1, 2022, pp. 15-24, DOI: 10.51519/ijbam.v5i1.542.

[9]. Devi Ajeng Efrilianda, Mustafid, R. Rizal Isnanto, "Inventory Control Systems with Safety Stock and Reorder Point Approach," 2018 International Conference on Information and Communications Technology (ICOIACT), Diponegoro University, Semarang, Indonesia.

[10]. Miss. Monali J. Nerkar, "A Review on Optimization of Material Cost through Inventory Control Techniques," International Research Journal of Engineering and Technology (IRJET), vol. 8, issue 8, Aug 2021, pp. 2395-0072.

[11]. Aurelija Burinskiene, "Forecasting Model: The Case of the Pharmaceutical Retail," Frontiers in Medicine, vol. 9, 2022, DOI: https://doi.org/10.3389/fmed.2022.582186.

[12]. Scott Veldhuizen, Laurie Zawertailo, Anna Ivanova, Sarwar Hussain, Peter Selby, "Seasonal Variation in Demand for Smoking Cessation Treatment and Clinical Outcomes," Nicotine & Tobacco Research, vol. 23, issue 6, June 2021, pp. 976-982, DOI: 10.1093/ntr/ntaa214.

[13]. Haile Yirga Mengesha, Getachew Moges Gebrehiwot, Birhanu Demeke Workneh, Mesfin Haile Kahissay, "Practices of anti-malaria pharmaceuticals inventory control system and associated challenges in public health facilities of Oromiya special zone, Amhara region, Ethiopia," BMC Public Health, 2021, DOI: https://doi.org/10.1186/s12889-021-12033-8.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25may1760

[14]. Konstantinos P. Fourkiotis and Athanasios Tsadiras, “Applying Machine Learning and Statistical Forecasting Methods for Enhancing Pharmaceutical Sales Predictions,” Forecasting, 2024.
[15]. Yasaman Ensafi, Saman Hassanzadeh Amin, Guoqing Zhang, Bharat Shah, “Time-series forecasting of seasonal items sales using machine learning – A comparative analysis,” Ted Rogers School of Management, Ryerson University, ON, Canada, Received 17 July 2021, Revised 12 January 2022, Accepted 12 January 2022, Available online 20 January 2022, Version of Record 20 January 2022.
[16]. Raheel Siddiqui, Muhammad Azmat, Shehzad Ahmed, Sebastian Kummer, “A hybrid demand forecasting model for greater forecasting accuracy: the case of the pharmaceutical industry,” Supply Chain Forum: An International Journal, vol. 23, no. 2, pp. 124-134, 2022, DOI: 10.1080/16258312.2021.1967081.
[17]. Ashutosh Kumar Dubey, Abhishek Kumar, Vicente García-Díaz, Arpit Kumar Sharma, Kishan Kanhaiya, “Study and analysis of SARIMA and LSTM in forecasting time series data,” Netaji Subhas Institute of Technology, Delhi, India, Received 25 August 2020, Revised 24 May 2021, Accepted 10 July 2021, Available online 28 July 2021, Version of Record 28 July 2021.
[18]. Jakob Huber, Heiner Stuckenschmidt, “Daily retail demand forecasting using machine learning with emphasis on calendric special days,” Data and Web Science Group, University of Mannheim, Available online 20 April 2020, Version of Record 16 September 2020.
[19]. UPPALA Meena Sirisha, Manjula C. Belavagi, Girija Attigeri, “Profit Prediction Using ARIMA, SARIMA and LSTM Models in Time Series Forecasting: A Comparison,” Department of Information and Communication Technology, Manipal Institute of Technology, Manipal Academy of Higher Education, Manipal, India, Corresponding author: Manjula C. Belavagi.
[20]. Nwokike, Chukwudike & Offorha, Bright & Obubu, Maxwell & Ugoala, Chukwuma & Ukomah, Henry. (2020). Comparing SANN and SARIMA for forecasting frequency of monthly rainfall in Umuahia. Scientific African. 10. 621. 10.1016/j.sciaf.2020.e00621.
[21]. Ensafi, Yasaman & Hassanzadeh Amin, Saman & Zhang, Guoqing & Shah, Bharat. (2022). Time-series forecasting of seasonal items sales using machine learning – A comparative analysis. International Journal of Information Management Data Insights. 2. 100058. 10.1016/j.jjimei.2022.100058.
[22]. Dubey, A. K., Kumar, A., García-Díaz, V., Sharma, A. K., & Kanhaiya, K. (2021). Study and analysis of SARIMA and LSTM in forecasting time series data. Sustainable Energy Technologies and Assessments, 47, 101474. https://doi.org/10.1016/j.seta.2021.101474
[23]. Belavagi, Manjula & Attigeri, Girija. (2022). Profit Prediction Using ARIMA, SARIMA and LSTM Models in Time Series Forecasting: A Comparison. IEEE Access. PP. 1-1. 10.1109/ACCESS.2022.3224938.
[24]. Wijesena, Dilanka & Bandara, Kapila & Tennakoon, Priyashantha & Wickramasinghe, Bhagya. (2023). Transformer Load Forecasting Method Based on SARIMA, FBProphet and LSTM Models. 1-6. 10.1109/ICIIS58898.2023.10253519.
[25]. Dubey, A. K., Kumar, A., García-Díaz, V., Sharma, A. K., & Kanhaiya, K. (2021). Study and analysis of SARIMA and LSTM in forecasting time series data. Sustainable Energy Technologies and Assessments, 47, 101474. https://doi.org/10.1016/j.seta.2021.101474