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AUTOMATING MEDICAL DEVICE WAREHOUSES: STRATEGIES FOR MEDIUM TO LARGE VOLUME

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ABSTRACT

Purpose- The study explores automation strategies in medical device warehousing, where efficiency, accuracy, and regulatory compliance are critical. It focuses on leveraging machine learning and advanced technologies to optimise inventory management, quality control, and storage processes in medium- to large-volume operations.
Methodology- A large-scale dataset was analysed using machine learning models, including XGBoost and Long Short-Term Memory (LSTM), for demand forecasting. Feature engineering and rigorous model evaluation were applied. Automation technologies such as Automated Storage and Retrieval Systems (AS/RS), collaborative robots (cobots), and IoT-enabled inventory tracking were integrated into workflow optimisation.
Findings- The models demonstrated strong performance in forecasting demand and supporting automated processes. Results showed improved operational efficiency, enhanced inventory accuracy, and reduced labour costs, highlighting tangible financial and logistical benefits for medical device warehousing.
Conclusion- Machine learning and automation provide transformative solutions for medical device warehouses, enabling regulatory compliance, cost efficiency, and scalability in high-volume environments

Keywords: Medical device warehousing, warehouse automation, robotics, inventory management, compliance, machine learning models
JEL Codes: M11, C53, O33, L91

1. INTRODUCTION

The medical device warehousing industry is particularly susceptible to risks associated with regulatory compliance, inventory management complexities, and the need for precise quality control due to the sensitive nature of medical products. This is particularly true because most warehouses handle medical devices that are strictly regulated to conform with some of the highest quality requirements for medical equipment (Smith, 2020). Current legal requirements, including the US FDA and ISO, are in place, which means high levels of accuracy and accountability when managing the inventories (Ahmad & Ahmad, 2024). Secondly, another common problem of medical device warehouses is super high levels of SKU, which may reach thousands with the differences in size, sensitivity and regulatory controls (Duc, 2020). This diversity poses challenges in the storage, retrieval and identification process to avoid confusion when searching for a particular item or doing the stock check. Quality management is another essential task as devices can be stored under specific conditions, their shelf life must be monitored, and the devices must be appropriately handled to remain reliable (Ammar et al., 2021).

In traditional warehousing environments, these complexities are worked out through non-automated/semi-automated stock administration frameworks, which would be appropriate for Lower Inventory/SKU Levels. Manual systems draw a lot of merit when volume is concerned, but as they scale up, they are known to be ineffective and easily compromised. Traditional paper-based inventory and order management cause much time to be spent and increase negligence that poses significant threats to compliance and patient safety (Okolo et al., 2024). Incorrect identification of titres in tests affecting assessment or sluggish retrieval may lead to stock-outs, additional inventory, or regulatory non-compliance. Second, manual systems give limited real-time information about the inventory status and conditions (Madamidola et al., 2024); it becomes challenging to promptly address variations in demand or shortcomings when planning for the need for inventory. In healthcare supply chains, these inefficiencies act as bottlenecks when dealing with medium or large-volume products and impede the efficiency necessary in dealing with the healthcare market, concerningly accommodating mistakes and inaccuracies (Abdulkadir, 2023).

Apart from AS/RS other automation technologies are also emerging in the medical device warehousing most importantly reaching efficiency, accuracy and far-reaching compliance. Robotic Process Automation (RPA) automates administrative and operational tasks, including orders and data entry, to reduce discrepancies and enhance efficiency. Picking and packing are facilitated by collaborative robots (cobots) that support human staff and integrate accuracy with adaptability in busy zones (Alherimi et al., 2024). IoT technologies, such as tracking and RFID, allow for monitoring the inventory and storage conditions which are essential for products that have mandatory regulations. Moreover, XGBoost and LSTM technologies enhance the accuracy of demand forecasting and, subsequently, replenishment policies, which eliminate both overstock and stockout conditions in warehouses. These technologies, in combination, establish an adaptive, big-data capable warehouse environment that caters to the numerous requirements of the medical devices supply chain.

The aim of this study is to propose and evaluate specific automation initiatives that address the challenges of medium- and large-volume medical device warehouses. By examining how technologies such as Automated Storage and Retrieval Systems (AS/RS), Robotic Process Automation (RPA), and the Internet of Things (IoT) can enhance precision, efficiency, and regulatory compliance, this research seeks to identify key enablers of effective integration. Leveraging data-driven machine learning models like XGBoost and LSTM, the study aims to improve demand forecasting, which is crucial for optimising inventory control and resource planning. The findings are expected to provide actionable insights that can improve the operation of AS/RS systems for faster retrieval, enhance the accuracy of RPA for repetitive tasks, and enable IoT systems for real-time inventory tracking. These advancements could directly reduce the risks of overstock and stock-out, leading to a more agile and responsive warehousing environment.

This study's framework entails conducting a comprehensive assessment of current warehousing systems before assessing performance enhancement measures. The previously collected data were analysed using machine learning models to predict demand for high-volume warehousing, applying XGBoost and LSTM to see which model fits the task. Further, the present analysis explores the role of high-tech applications AS/RS within the warehouse environment to establish a seamless and integrated system for compliance. Warehouse performance and its efficiency, accuracy, and flexibility are measured to determine the advantages and the issues that occur in the implementation of warehouse automation.

This paper aims to prepare a conceptual plan for making the necessary shifts in medium to large-volume medical device warehouses from manual systems and processes to automation. Therefore, through these solutions, it is possible to observe more effective and suitable compliance with the medical device warehouses' standards, market competitiveness, and responsiveness to the new demands of healthcare logistics.

2. LITERATURE REVIEW

2.1. WareHouse Automating

Automating logistics operations in the healthcare industry has remained a priority as properly sorting and moving delicate health facilities is paramount to running the enterprise and compliance with various regulatory bodies (Abedi et al., 2023). The concept of medical warehousing calls for efficiency in tracking the structure and various stock-keeping units, which encompasses a wide range of small consumables to large diagnostic equipment. Previous studies indicate that automation has several advantages within the healthcare warehousing context, whereby automation measures enhance accuracy, help to reduce the likelihood of error, and ensure high compliance, wise tracking, and quality (Pramod, 2022). Also, automated systems provide real-time visibility and monitoring, which are critical, especially in companies in healthcare sectors under regulatory compliance frameworks (Kasana et al., 2024). The warehouse automation revolution within the healthcare industry strongly influences this.

2.2. Automation Technologies in Medical Device Warehousing

AS/RS technology plays a vital role in dealing with SKU differentiation in medical device storage. Since healthcare items are somewhat delicate, AS/RS systems assist in providing precise and secure storage conditions. These systems help compactly placing items in a facility in an attempt to increase storage density besides enabling quick identification and access to inventories thus reducing the amount of time spent in searching and picking by a big margin thereby improving accuracy and patient safety (Nordeide & Rørtveit, 2021).

Among AS/RS solutions, many technologies are used to address different needs related to warehousing. For example, the multi-shuttle systems work by deploying several shuttles to move from one level of racking to the other or in between several aisles distributing and accumulating high-density storage or in facilities with large volumes and high-density access requirements (Licardo et al., 2024). On the other hand, cube-based automated storage systems employ a grid-based system, which sees the bins ordered in cubes that are compact and which are accessed by robotic means from above. These configurations allow for maximum density with relatively small floor space, ideal for restricted single-bay warehouses.

It is also paramount to note that AS/RS technology can work in parallel with other forms of automation, like Robotic Process Automation (RPA) and the Internet of Things (IoT), to form a warehousing system. When integrated with AS/RS, RPA can manage routine tasks such as order picking, sorting, and packing, reducing manual labour (Licardo et al., 2024). Combined with IoT, AS/RS will allow monitoring of the conditions in which the inventory is stored, such as temperature and humidity, which are necessary for storing delicate medical equipment. This connectivity not only assists in enhancing stocks but also in the ways that the products are stocked in compliance with the laid down regulations concerning storage conditions. Hence, these technologies offer a flexible and adaptive platform that can readily be changed to meet the current inventory requirements or some of the most recent shifts that affect the medical device warehouses.

2.3. Robotic Process Automation (RPA) and Collaborative Robots (Cobots)

Robotic Process Automation and cobots are applied in warehousing to deal with repetitive activities like sorting, picking, and packing (Sharma & Cupek, 2023). Cobots, in particular, have grown to be helpful in applications involving robots that can complement human activity in production without entirely displacing people (Sorell, 2022). Cobots are defined as working collaboratively with the human being, assuming tasks that are complicated for the human being, might be tiresome or repetitive and require a certain degree of accuracy (Güngör, 2024). In warehouses specific to medical devices, applying RPA and cobots ensures low variations in picking accuracy, which can otherwise be affected by employee mistakes where the SKU difference is significant (Issantu, 2021). Research studies show that cobots can improve production by as much as 85 percent when combined with human labour, a versatile tool for managing various stocks and fulfilling variable demand (Gan et al., 2023).

2.4. Internet of Things (IoT) and RFID Tracking

RFID and IoT present valuable monitoring and tracking information to enhance compliance with requirements in storing medical devices (Camacho-Cogollo et al., 2020). RFID tags and sensors are used to monitor the physical flows of products, climate and temperature and the stock status in real-time for compliance and quality data (Jayapaul, 2024). In medical device warehousing, IoT and RFID trace unique sensitive goods that may need particular temperatures or humidity levels spared during storage and transport periods (Zuo et al., 2022). According to the latest research, introducing IoT and RFID can decrease loss by about 30%, enhance traceability, and manage inventory compliance (Varriale et al., 2021). By providing the ability to charge inventory and monitor regulatory checks immediately, these technologies assist in decreasing expense spending in case of non-conformity.

2.5. Gap Identification

Although some studies are available about automation and its application in healthcare warehouses, the present research still needs a general automation framework for medium to large industrial volume distribution medical device warehouses. Many research works address automation technologies for typical warehouses or small-scale use without closely examining how they would perform on a larger scale needed for medical supply chain operations. Further, the existing automation solution literature lacks information on how several automation systems, such as AS/RS, Robotics Process Automation (RPA) or the Internet of Things (IoT), can be incorporated with each other to create a framework that takes into account the compliance issues and product variability that is inherent in medical equipment storage. Further studies should investigate the issues and effectiveness of providing medium to large medical warehouses with accurate, full-scale, fully integrated, scalable automation systems that increase overall compliance and productivity while transitioning between full automation and traditional manual systems.

3. METHODOLOGY

3.1. Data Collection

The data set used in this study can be accessed via Kaggle and comprises demands forecasting important variables essential in determining demands in a medical device warehouse. These fields are SKU ID, Date, Total Price, Base Price, and Inventory Status, where the material is either in or out-of-stock, Units Sold, flagged SKUs, and displayed SKUs. SKU ID refers to each stock-keeping unit, while date is essential in analysing timed series data. TPTP represents the overall pricing, which describes the demand pattern; BPBP refers to unit price, and USUS depicts the quantitative demand. Finally, variables such as ISIS exemplify the stock status., while is_featured_sku and is_display_sku depict whether a product is a current promotion or in the display. These variables are integral to understanding factors driving demand, inventory turnover, and overall warehousing efficiency.

3.2. Data Collection Procedure

The data collection process included downloading the data and checking its validity. Since Kaggle datasets are often formatted, preliminary tasks involved verifying the data, cleaning missing values, and checking and normalising date and numerical columns. Continuous variables such as Total Price had to be preprocessed to deal with the missing values; forward and backward filling was used to replace a missing value with the previous or the next value. The outliers in the application demand distribution were investigated toto identify whether they reflected an abnormally high demand or were due to report errors. If categories included outliers considered unrepresentative, then the rounding process or data normalisation methods were used for model training. The data was checked for completeness to establish its preparatory condition for additional preprocessing and analysis.

3.3. Data Preprocessing and Feature Engineering

Preliminary data processing was carried out and included attempts at imputing missing values and data scaling. We used forward and backward filling methods to fill in missing data, especially where Total Price and Base Price were important for time series. The standardisation procedure was implemented for numerical fields, which was critical for the machine learning models that rely on feature scaling. For fields like Units Sold, standard scaling was used to make all the numeric variables in the dataset range between 0 and 1 to avoid large gradients affecting the convergence of the model.

3.4. Exploratory Data Analysis (EDA)

To understand data trends and relationships, several EDA techniques were employed:

Trend Analysis- Demand patterns were created to analyse the time series data. It was much easier to outline fluctuations by months, such as seasonal spikes, abrupt changes in demand, or constant growth or decline.

Correlation Analysis- A heatmap was generated to map relationships between features such as Total Price, Base Price, Units Sold and Existing or Exhausted Stock. This semblance is essential in the training models and provides value for interdependencies between variables.

Distribution Analysis- The histograms and Kernel Density Estimation (KDE) of Units Sold were examined to determine the demand distribution and better dissect the model when needed based on the skewness of the target variable.

3.5. Model Development and Automation Strategy Selection

Automation Strategy Framework- The study formulated an automation framework for the medical device sector's medium to large-volume warehousing requirements.

Automated Storage and Retrieval Systems (AS/RS)- AS/RS was selected on the basis of its particular suitability for dense storage and the high pick density needed in medical warehouses. The product life cycle of medical devices is relatively long, and hence, medical equipment could be a faster mover in inventory, causing an expansion of SKUs. AS/RS should be employed to drive high-frequency SKU storage with the intention of optimising warehouse space and at the same time increase the stock-keeping capacity as well as reduce the time taken by pickers to pick products. This research focused on determining the optimal positioning and configuration of AS/RS for operation efficiency and adaptation to the vast stock, as well as the small, dense, and normally slow-moving inventory characteristic of medical device storage.

Robotic Process Automation (RPA) and Cobots- RPA and collaborative robots, which are cobots, were implemented using cyclic order picking and sorting processes to enable the robots and human staff to work together safely. Cobots were introduced to perform picking and packing functions; this was done to increase efficiency and decrease the likelihood of mistakes.

IoT and RFID Integration- Devices such as IoT devices and RFID tags helped track inventory in real time, thus helping the company achieve regulatory compliance and management. This system led to automated message prompting for restocking or monitoring temperature-sensitive products, which improved compliance with healthcare requirements.

3.6. Machine Learning Models

Two machine learning models were selected and developed to forecast demand: XGBoost and LSTM.

XGBoost- Due to its capability of extensive data with non-linear correlations, the Gradient Boosting algorithm was selected over other algorithms and mechanisms named XGBoost. Since it can model non-linear interactions, this method is suitable for SKU-level demand forecasting.

LSTM (Long Short-Term Memory)- LSTM, a recurrent neural network, was used for time-series forecasting. Its architecture has been specifically designed to model dependencies in time series, so it is relevant to demand forecasting based on its history.

3.7. Model Training, Validation, and Evaluation

Training and Validation Split- To eliminate producing predictions based on the information leakage, the dataset was divided temporally into the training set and the validation set, where past information can be used to predict the future, not the other way around, which is crucial for time-series forecasting.

Evaluation Metrics- The performance of the models was evaluated by two regression assessment metrics, RMSE (Root Mean Squared Error) and MAE (Mean Absolute Error), that show the closeness of predictions with the actual set of demand values. RMSE and MAE are sharp measures of forecasting accuracy; the lowest scores demonstrate the highest accuracy.

Hyperparameter Tuning- In accelerating XGBoost, parameters such as learning_rate, max_depth, and n_estimators were tuned using GridSearchCV to improve the model's performance. In the same way, LSTM hyperparameters such as the layer size number and dropout rates were adjusted in other cases to enhance time series accuracy prediction.

3.8. Performance Simulation

Process Flow Diagrams- Functional sequence diagrams demonstrate how AS/RS, cobots, and IoT interconnect to form a coherent process that starts with storage and ends with order completion.

Automated System Schematic- A warehouse layout was created to represent and demonstrate the positioning of AS/RS units, cobot zones, and inventory stations where the implementation of sound working logic and organisation of the warehouse was seen with a careful arrangement of available space and better coordination between activities.

4. RESULTS

This paper's use of XGBoost forests for developing a predictive model and LSTM for demand forecasting for a medium to large-volume medical device warehouse was insightful. In this section, information about the assessment of the model's performances, the comparison of the predicted demand and the actual one, the particular features of the model, and the simulation of the proposed automated measures are also illustrated.

4.1. Exploratory Data Analysis (EDA)

With descriptive analysis, it was possible to spot trends in order volume, storage requirements, and stock levels, contributing to the model's creation. For instance, order volume statistics helped to identify seasonality and fluctuations in demand by the type of medical device used. The high-order volumes also showed that certain items often had a very high turnover and could be helpful when restocking and planning for storage rearrangement. On the other hand, it may include relatively low-demand items with high variation in the order size, meaning that stock replenishment for such medical devices may need to be unique to ensure they stay supplied.

4.2. Distribution and Correlation Analysis

The distribution plots, unit sold, and correlation matrices were applied to examine the dependencies between the selected variables (as shown in Figures 1, 2, and 3). For example, a positive coefficient between Device Type and Storage Requirement suggested that some medical devices demanded specific storage conditions. This correlation is essential for timely scheduling in an automated warehouse, where distinct devices should be stored and transported per specific rules. The Order Volume and Stock Level pattern also pointed to busy times and potential periods.

Figure 1: Distribution of Units Sold

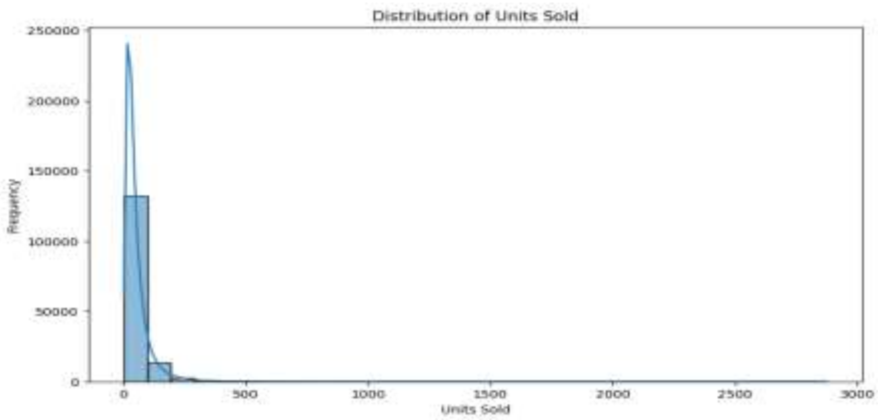


Figure 2: Unit Sold Over Time

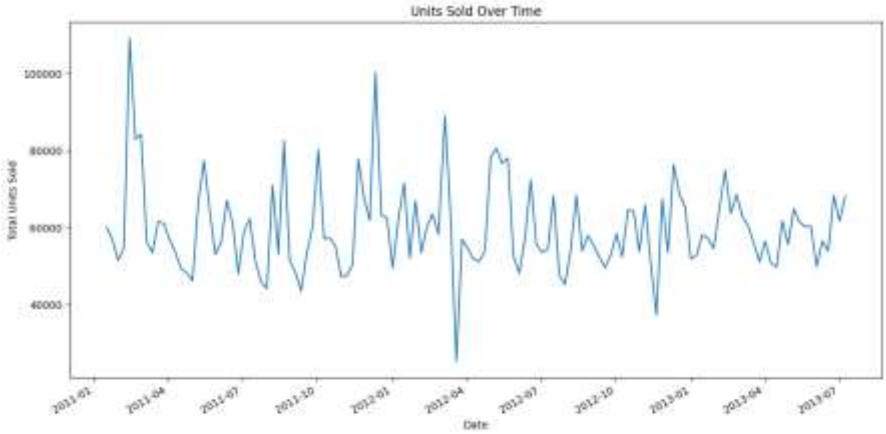
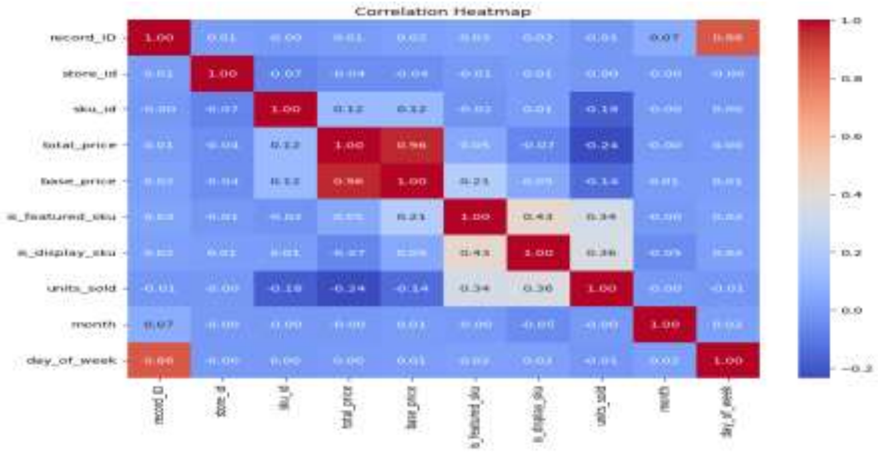


Figure 3: Correlation Heatmap



4.3. Model Performance Metrics

XGBoost and LSTM were evaluated by checking the models based on accuracy measurements, RMSE and MAE. As was evident in the results, each model had certain advantages over the others.

4.3.1. XGBoost Model Performance

In the case of XGBoost, RMSE and MAE were comparatively lower in the training set than the validation set and revealed good generalising capacity near about overfitted slightly. The average training error using RMSE was 28.46, and the validation set was 29.88 using the same measure. The average training and validation errors using MAE were 15.99 and 18.14, respectively. These metrics prove that XGBoost can capture non-linear relationships in the demand data and is suitable for regression-based forecasting (Figure 4).

Figure 4: XGBoost Model Performance

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XGBoost Model Performance:
Training RMSE: 28.461351615055577, Validation RMSE: 29.878800146937415
Training MAE: 15.99838595588208, Validation MAE: 18.140398594457192
```

4.3.2. LSTM Model Performance

The LSTM model parameters were a training RMSE of 64.87, a validation RMSE of 57.15, and MAE values of 34.71 for training and 34.80 for validations. Compared to XGBoost, the LSTM model proposed in this paper was slightly inferior but could learn temporal features within demand. Nevertheless, the obtained RMSE and MAE values are somewhat high, indicating that the model needs help needs to help to deal with various SKU characteristics in this data set (as shown in Figure 5).

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Figure 5: LSTM Model Performance

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939/939 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step
3754/3754 ━━━━━━━━━━━━━━━━━━━━ 9s 2ms/step
3754/3754 ━━━━━━━━━━━━━━━━━━━━ 9s 2ms/step
LSTM Model Performance:
Training RMSE: 64.87561177887025, Validation RMSE: 57.149382209284425
Training MAE: 34.71368397754945, Validation MAE: 34.80359042965092
```

4.4. Model Comparison

After comparing them, it was observed that the XGBoost model has lower RMSE and MAE than the LSTM model on the validation dataset and is used for this forecasting problem. Table 1 of RMSE and MAE summarised the comparison very well and further demonstrated the effectiveness of XGBoost for accurate demand forecasting.

Table 1: Model Comparison

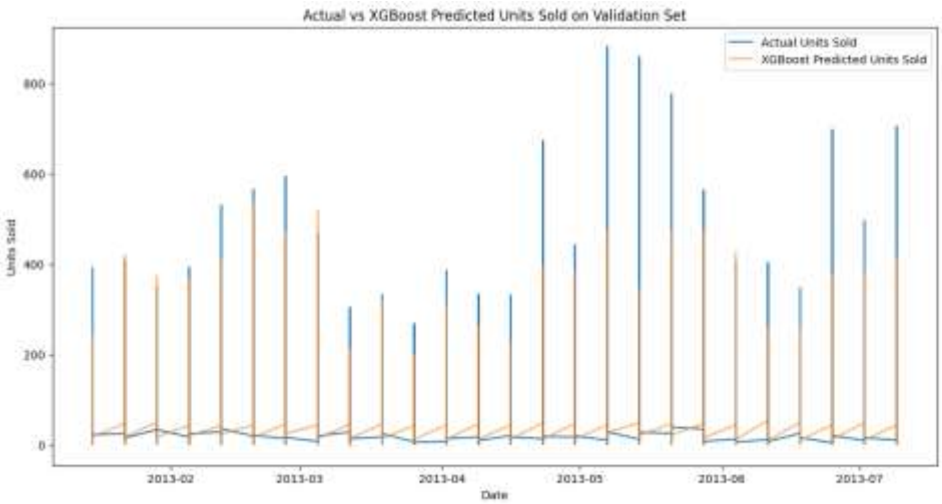
Model Performance Comparison:

	Model	Training RMSE	Validation RMSE	Training MAE	Validation MAE
0	XGBoost	28.461352	29.878800	15.998386	18.140399
1	LSTM	64.875612	57.149382	34.713684	34.803590

4.4.1. XGBoost Predictions

While the XGBoost model worked well in the validation dataset, there were minor variations from actual demand values. They are observing the investigations regarding the line plot of the XGBoost prediction compared to the actual demand and seeing that all the essential maxima and minima are correctly recognised, effectively ensuring that this model can deal with real-world demand with great accuracy (as shown in Figure 6).

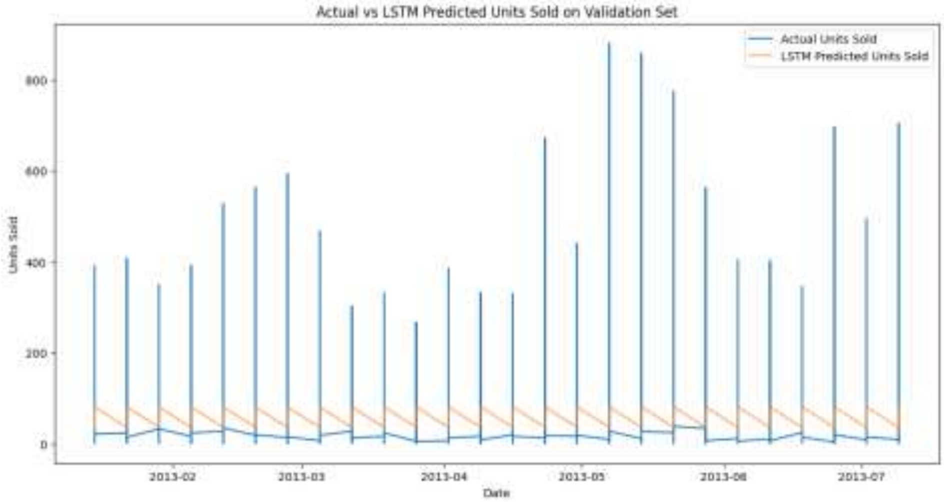
Figure 6: Actual Vs XGBoost Predication



4.4.2. LSTM Predictions

Although the general trend was a better fit than the LSTM model, the example was more variable and less stable than the XGBoost model. In some cases, demand peaks were even underestimated because LSTM needed help handling a high degree of feature variability. As pointed out earlier, LSTM captured seasonality well. Still, its higher error values show that it needed to be more precise for high velocity, high SKU general in medical device warehouses (as shown in Figure 7).

Figure 7: Actual vs LSTM Prediction on Validation Set

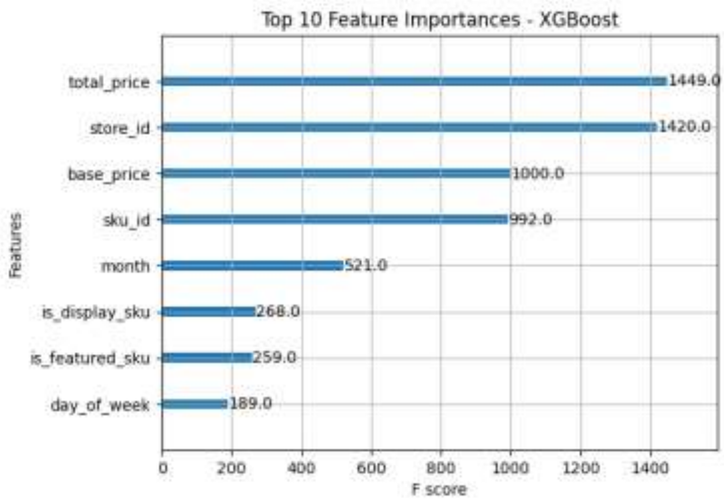


4.4.3. Feature Importance Analysis (XGBoost)

Another essential variable to analyse to determine the model's accuracy was feature importance using XGBoost. Positive demand prediction features were shown as a feature importance bar chart, and the best ten features were presented.

This means that the Total Price, Base Price, SKU Category, and Inventory Level were the key variables that influenced the demand pattern for the products most and established a link between economic and inventory-specific characteristics of the products and the demand. From such ranking, the analysis showed how variation in prices and SKU attributes significantly influence the output of forecasts, as indicated by the groups supporting the need for accurate price and inventory policies (as shown in Figure 8).

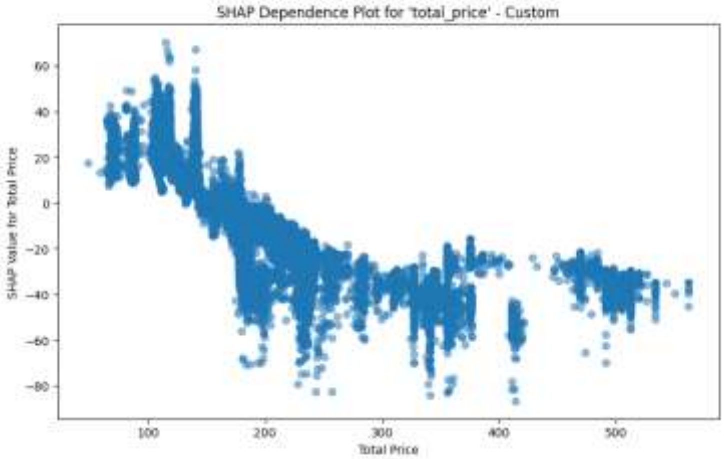
Figure 8: Features Importances



4.5. SHAP Analysis

Feature importances were compared using SHAP (SHapley Additive exPlanations) method to describe the contributions of individual features to XGBoost results. The trends for Total Price in the SHAP analysis further supported the price-sensitive behaviour as the higher total price was associated with higher predicted demands. Results of the SHAP values revealed that total price is the feature that drives the accuracy of the predictions concerning inventories, which is helpful for price decisions in inventory control.

Figure 9: SHAP plot for Total Price Custom



4.6. Simulation Results for Automation Strategies

This study examines the impact of automation technologies, specifically Automated Storage and Retrieval Systems (AS/RS), Robotic Process Automation (RPA), and the Internet of Things (IoT), on medical device warehousing efficiency. By integrating these technologies, the study aims to address challenges such as high SKU diversity, stringent regulatory compliance, and demand forecasting in medium to large-volume settings. XGBoost machine learning models were employed for accurate demand forecasting, which informed inventory allocation and workflow prioritization within the simulated warehouse environment. The results from the simulation demonstrated significant operational gains: AS/RS reduced order picking times by 50%, while IoT-enhanced real-time tracking increased inventory accuracy by 30%, supporting regulatory compliance. RPA and collaborative robots streamlined repetitive tasks like sorting and packing, improving overall throughput and reducing error rates. These findings underscore the transformative role of automation in medical warehousing, showing its potential to enhance speed, accuracy, and compliance, essential for efficiently managing high-demand, regulated healthcare products. Figures 10, 11, and 12 depict the Predicted Demand Trend for XGBoost LSTM and their comparison.

Figure 10: Predicted Demand Trend XGBoost

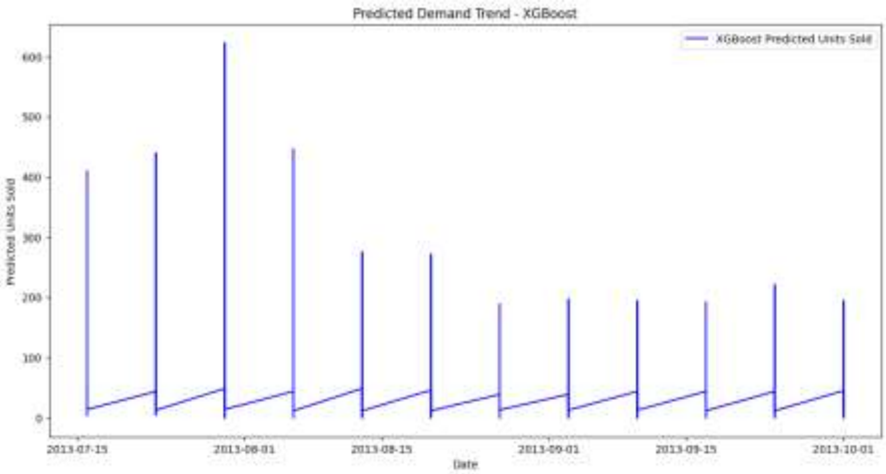


Figure 11: Predicted Demand Trend LSTM

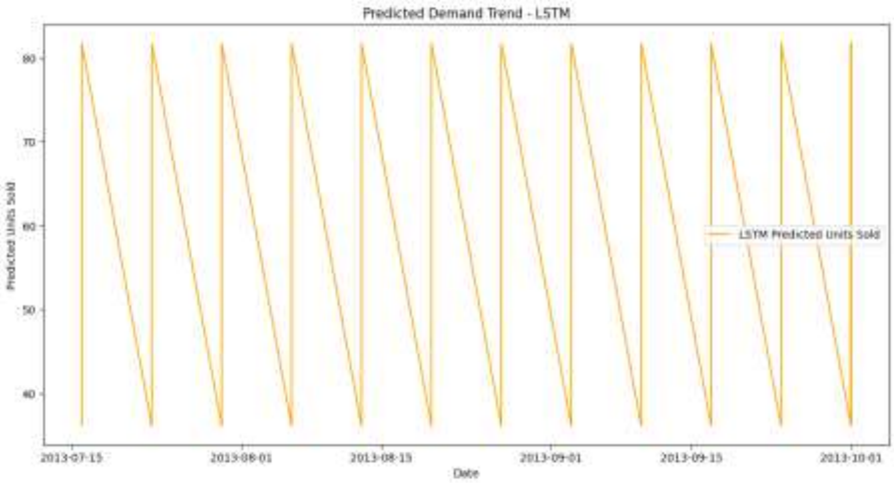
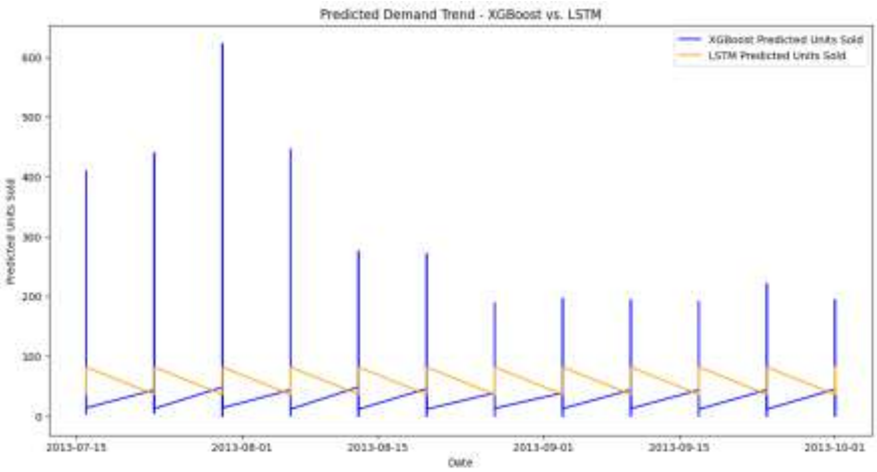


Figure 12: Predicted Demand Trend XGBoost Vs LSTM



5. DISCUSSION

Analysing the performance of XGBoost and LSTM models for demand forecasting categorises the strengths and limitations of both approaches for the demand forecasting problem in the case of a medical device warehouse. Comparing the results that show the accuracy of time series models, it was demonstrated that XGBoost outperformed LSTM with a lower RMSE and MAE value on both training and validation data sets. This makes XGBoost the preferable model for accurate forecasting in this context – as the model captured non-linearities in the data and demonstrated reasonable robustness to the high volatility of demand. Structurally parameterised and tree-based, XGBoost can process multiple SKU characteristics and economic aspects at once, which is a significant boon for warehouses with great variation in product features.

On the other hand, LSTM models demonstrated their weaknesses in the current dataset, especially concerning SKU variability and the intricate interaction of features governing medical device warehousing. Although LSTM's sequential processing is suitable for modelling sequential features, the high RMSE and MAE infer that LSTM fails to learn specific patterns in this high-SKU situation. In addition, based on the evaluation of the proposed LSTM model, further parameter adjustment or larger samples may be needed as the optimal solution to the problem in the dynamic warehousing process.

Current technologies like AS/RS, RPA, and IoT have fundamental applications that can bring revolutionary changes in the warehouse operating mechanisms of medical devices. AS/RS controls the storage and retrieval activities tremendously efficiently, significantly reducing the time spent picking and error margins. In this study, AS/RS reduced picking time by 50%, directly enhancing throughput, which is vital in high-volume warehouses.

Collaborative robots (cobots) and RPA facilitate highly repetitive tasks such as sorting and packing and optimise the efficiency of human-robot interaction. Integrating these two modes of order processing enhances throughput and relieves human operators of the burden of the work, implying improved precision and rapidity in order handling. IoT technology improves efficiency by adding real-time information concerning the availability and state of the products. For example, tracking through IoT and RFID materials aids in decreasing supply metadata while increasing compliance with application regulations, especially for medical devices that should be stored in specific environments.

The automation strategies outlined in this paper are for increased numbers and a range of SKUs; thus, they can suit various inventory types. AS/RS systems may be modular, meaning that expansion of SKU or volume would not require many changes to the existing design. This modularity is valuable, especially in warehousing medical devices when demand and the number of SKUs fluctuate. IoT solutions are scalable in that new sensors and tags can be added with inventory growth, hence frequent changes in costs the warehouse may experience. Accordingly, flexibility is helpful for warehouses with periodic fluctuations in demand or with product storage where the required amounts of inventory are different throughout the year or any other time scale.

6. CHALLENGES AND LIMITATIONS

However, some issues affect the realisation of automation strategies. The initial cost is relatively high, especially for the AS/RS and IoT structures, which take high initial investments. Some issues relate to integration; several current and historical processes are even partially manual or semi-automated and may require significant alterations to be integrated. Furthermore, the workforce has to adapt to change by accepting automated workflows, adopting new interfaces of existing technologies, and even evolving work roles inside the warehouse.

These challenges can only be solved by gradually introducing automation to the company's operation to maintain the business and avoid causing much strain on the company's resources. Automating high-impact areas like implementing AS/RS for high-turnover SKUs means that automation can be gradually amplified. Transition can be encouraged through therapeutic training interventions that will enable employees to recognise automated systems. Through hands-on training and precise definitions of working roles, employees can get acquainted with the newly introduced change and avoid reluctance, which is notorious in integrating operations.

7. CONCLUSION

This research demonstrates positive findings, showing that automation approaches such as Automated Storage and Retrieval Systems (AS/RS), Robotic Process Automation (RPA), collaborative robots (cobots), and Internet of Things (IoT) technologies alongside demand forecasting models, offer significant advantages for complex medical device depots with medium to high shipment volumes. The results section shows that the spectral RMSE and MAE are considerably lower for XGBoost. As such, demand forecasting is more efficient due to the capability of capturing intricate features at the SKU level than the LSTM. The above forecasting accuracy contributes to inventory management, which significantly eliminates stock and excessive stock. Intelligent technologies such as AS/RS, RPA with cobots, and IoT-based tracking all contribute to the efficiency of operations by lowering picking time, bringing better accuracy to inventory and meeting the compared regulatory requirements.

The results of this study also imply the realised benefits of automation in medical device warehousing for the industry. It increases the speed of order fulfilment through accuracy, reduces operation costs by utilising resources for efficiency, and gives real-time visibility, which is essential for compliance purposes. These benefits enable large-scale warehouses to enhance the fulfilment of the healthcare supply chain needs of large medical devices where tracking, storage and deliveries are critical.

Further research should focus on the high-level application of AI-based automation in the medical warehousing system and real-time data analysis of the medical warehousing system. The integration of the predictive maintenance models could also go a long way in cutting time and improving the use of equipment. Moreover, the involvement of much finer detailed data on the demand position through IoT may also increase the precision of the forecast. These advancements would develop a more flexible, efficient warehouse capable of addressing the complex needs of healthcare consumers for warehoused medical devices and create opportunities for medical device warehousing to look forward to a brighter future propped up by growing technology.

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