

AI-Based Medicine Shortage Prediction Using Machine Learning

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Abstract: *Medicine shortages can create serious problems in healthcare facilities because patients may not receive medicines when they are needed. Predicting medicine shortages in advance can help healthcare facilities take timely action and improve medicine availability. This research presents an AI-based approach for predicting future medicine shortages using machine learning techniques and healthcare inventory data from Sierra Leone. The dataset contains information related to medicines, healthcare facilities, districts, dates, received quantity, consumption, opening balance, and previous stockout status. After data preprocessing and medicine selection, a future shortage target was created to predict whether a medicine shortage would occur in the following month. Three machine learning models, namely Random Forest, Gradient Boosting, and XGBoost, were developed and evaluated. The models were evaluated using Accuracy, Precision, Recall, F1-score, and ROC-AUC. To examine the ability of the models to work with healthcare data from different geographical areas, a cross-district evaluation was also performed using districts that were not included during model training. The results show that machine learning can identify patterns in healthcare inventory data that are useful for predicting future medicine shortages. The proposed approach can support healthcare facilities in identifying potential shortages earlier and can contribute to better medicine inventory planning and availability.*

Keywords: Medicine Shortage Prediction, Machine Learning, Artificial Intelligence, Healthcare Inventory, Stockout Prediction, Sierra Leone, Cross-District Generalization, Healthcare Data

I. INTRODUCTION

Medicines are an important part of healthcare services, and their continuous availability is necessary for providing appropriate treatment to patients. However, medicine shortages and stockouts remain a major challenge for healthcare systems. The World Health Organization (WHO) has reported that shortages and stockouts of essential medicines can occur in countries at different income levels and may affect healthcare delivery and patient outcomes.

Medicine shortages can occur due to different factors, including problems in supply chains, changes in demand, manufacturing issues, procurement difficulties, and limited information about future supply conditions. WHO defines a stockout as the complete absence of a medicine at the point of service delivery, while a shortage refers to an insufficient supply to meet healthcare and patient needs. These problems make effective medicine inventory management important for healthcare facilities.

Traditional inventory management generally depends on historical records and current stock information to make supply decisions. However, the increasing availability of healthcare data provides an opportunity to use data-driven methods for identifying patterns related to medicine shortages. Machine learning can analyze historical inventory information and learn relationships between different factors that may be associated with future shortages. This can help healthcare facilities identify potential shortages before they occur and support more timely inventory planning.



In this research, a machine learning-based approach is developed for predicting future medicine shortages using healthcare inventory data from Sierra Leone. The dataset contains information related to medicines, healthcare facilities, districts, dates, received quantities, consumption, opening balance, and previous stockout status. These variables are used to identify patterns associated with the occurrence of shortages.

A major focus of this study is the ability of the prediction models to work across different geographical areas. Healthcare data may vary between districts because healthcare facilities can differ in their facility type, medicine consumption, supply patterns, and stock conditions. Therefore, the study includes a cross-district evaluation in which the trained models are tested on data from districts that were not used during model training. This provides an additional assessment of whether the learned patterns can be applied to healthcare data from different districts.

Three machine learning algorithms, Random Forest, Gradient Boosting, and XGBoost, are developed for the prediction task. The models are evaluated using Accuracy, Precision, Recall, F1-score, and ROC-AUC. The study aims to examine the usefulness of machine learning for one-month-ahead medicine shortage prediction and to evaluate its performance when applied to healthcare data from different districts.

II. LITERATURE REVIEW

Several researchers have investigated the use of predictive analytics and machine learning for identifying and managing medicine and drug shortages. These studies provide a foundation for developing data-driven approaches for early shortage prediction.

Liu et al. (2021) developed and validated a predictive model to identify drugs at high risk of shortage. The study used internal purchasing, formulary, and drug shortage data from a healthcare organization in the United States. The researchers considered drug characteristics and manufacturing-related factors as potential predictors. The model achieved an accuracy of 0.87 and a C-statistic of 0.93 in the reported evaluation. The study demonstrated that predictive analytics can support a shift from reactive to more proactive drug shortage management.

However, the model mainly focused on drug and manufacturing characteristics rather than healthcare inventory conditions across different geographical areas.

Pall et al. (2023) developed machine learning models for predicting drug shortages using sales data from 22 Canadian pharmacies and historical shortage information. Their models predicted shortage classes one month in advance and achieved 69% accuracy for the four-class shortage prediction task. The study also correctly predicted 59% of shortages considered to have the greatest impact. Important variables included previous shortages, days of drug supply, and demand-related information. This study is particularly relevant to the present research because it demonstrates the usefulness of machine learning for early medicine shortage prediction. However, it was based on Canadian pharmacy data and did not specifically examine whether the learned patterns could generalize across different healthcare districts.

Dong et al. (2023) developed and validated a prediction model for assessing the risk of hospital drug shortages. The study used drug procurement data and considered factors such as therapeutic class, dosage form, distribution firm, order information, and unit price. A training and validation approach was used to evaluate the model, with ROC-AUC used to measure discrimination. The reported AUC was 0.707 for the training set and 0.688 for the validation set. The study showed that several procurement and drug-related factors can be useful for identifying shortage risk. However, the study focused on a single hospital setting and did not evaluate model performance across different districts or healthcare facilities.

Joshi et al. (2025) examined the application of machine learning in hospital pharmacy for predicting drug shortages and improving supply-chain management. The study discussed several machine learning approaches, including Random Forest, Gradient Boosting Machines, and Long Short-Term Memory models. It emphasized the use of historical data, demand patterns, seasonality, and supply-related factors to identify potential shortages and improve inventory planning. The study also highlighted challenges related to model interpretation and integration with existing healthcare systems. This work supports the use of machine learning models for healthcare inventory and shortage prediction.



Park et al. (2025) developed machine learning models using 1,054 drug-shortage cases reported to the Korean Ministry of Food and Drug Safety from 2018 to 2024. The study developed one model to predict shortage-duration ranges and another to classify shortage causes into seven categories. Eighteen features were used, and Random Forest feature importance was applied to identify important predictors. The duration prediction model achieved 62% accuracy, while the cause-classification model achieved weighted precision, recall, and F1-scores above 70%. The study demonstrates that machine learning can be used not only to identify shortages but also to analyze their characteristics and causes. However, its data were based on regulatory shortage reports rather than facility-level healthcare inventory data.

Angula and Dongo (2024) conducted a systematic review to examine the use of artificial intelligence and machine learning for forecasting medication demand and supply in public pharmaceutical systems. The review examined 13 peer-reviewed studies and discussed different approaches for predicting medicine quantities and improving pharmaceutical inventory management. The findings indicated that Random Forest and linear regression were commonly used for medication forecasting. The authors also identified challenges related to data quality, fluctuations in medicine demand, privacy, and the implementation of predictive models. This study supports the use of machine learning for medicine inventory planning. However, it focused on forecasting medication demand and supply rather than directly testing medicine shortage prediction across previously unseen geographical districts.

Agada (2024) investigated the prediction of pharmaceutical needs in hospitals using three years of historical data from a government hospital in Jos. The study used Random Forest and neural network algorithms to predict medicine types and quantities. The Random Forest model achieved 83.3% accuracy when predicting medicine quantities for a one-month period, while its accuracy for predicting medicine types was 35.9%. The findings demonstrated the potential of machine learning for forecasting pharmaceutical requirements and supporting hospital inventory decisions. However, the study focused on predicting pharmaceutical needs within a hospital rather than directly predicting future medicine shortages across multiple healthcare districts.

The reviewed studies demonstrate that predictive analytics and machine learning can be useful for identifying drug shortage risks and supporting healthcare inventory management. Existing research has used pharmacy sales, procurement information, drug characteristics, pharmaceutical demand, and supply-chain factors for prediction. However, most studies have focused on specific hospitals, pharmacies, or national-level shortage databases. Limited attention has been given to using facility-level healthcare inventory data and testing whether a machine learning model can generalize to different geographical districts.

The present study addresses this area by using healthcare inventory data from Sierra Leone and predicting future medicine shortages using Random Forest, Gradient Boosting, and XGBoost. In addition to standard model evaluation, the study performs a cross-district evaluation to examine whether the models can identify shortage patterns in districts that were not used during model training.

Research Gap

Existing studies have shown that machine learning can be used for predicting medicine shortages using pharmacy, hospital, procurement, and shortage-report data. However, limited research has focused on using facility-level healthcare inventory data across different districts for one month-ahead medicine shortage prediction.

Healthcare conditions and inventory patterns may vary between districts due to differences in facility types, medicine consumption, stock levels, and supply conditions. Therefore, it is important to examine whether a machine learning model trained on some districts can also perform effectively on data from previously unseen districts.

This study addresses this gap by using healthcare inventory data from Sierra Leone and evaluating Random Forest, Gradient Boosting, and XGBoost models for future medicine shortage prediction with a cross-district evaluation.



Research Objectives

The main objectives of this research are:

- To develop a machine learning-based approach for predicting future medicine shortages using healthcare inventory data.
- To use inventory-related factors such as medicine consumption, received quantity, opening balance, and previous stockout information for shortage prediction.
- To develop and compare Random Forest, Gradient Boosting, and XGBoost models for one-month-ahead medicine shortage prediction.
- To evaluate the performance of the developed models using Accuracy, Precision, Recall, F1-score, and ROC-AUC.
- To examine the ability of the trained models to generalize to healthcare data from previously unseen districts.

III. RESEARCH METHODOLOGY

This study proposes a machine learning-based approach for predicting future medicine shortages using healthcare inventory data from Sierra Leone. The methodology consists of data preprocessing, medicine selection, feature engineering, future shortage target creation, healthcare data analysis, model development, cross-district evaluation, and model performance evaluation.

Research Design

The study follows a quantitative and data-driven research design. Historical healthcare inventory records are analyzed to identify patterns related to medicine availability and stockouts. Machine learning classification models are then developed to predict whether a medicine shortage will occur in the following month.

Dataset Description

The study uses healthcare inventory data from Sierra Leone. The dataset contains information related to medicines, healthcare facilities, dates, stockout status, received quantity, consumption, opening balance, closing balance, facility type, and district. The dataset contains 36 medicine products, 1,091 healthcare facilities, and 16 districts, covering the period from October 2019 to November 2023. For the final prediction analysis, 25 medicine products were selected.

Data Preprocessing

The raw data were first cleaned and prepared for analysis. The date information was converted into a suitable format, and relevant time-related features such as month, year, and quarter were extracted. The records were organized according to medicine, healthcare facility, and date. The selected medicine products were then filtered and the relevant inventory variables were retained for further analysis.

Feature Engineering

Relevant healthcare inventory and time-related variables were used as input features for the machine learning models. These include medicine information, healthcare facility, facility type, district, month, year, received quantity, consumption, opening balance, and previous stockout information. The records were arranged chronologically for each medicine and healthcare facility so that information from the current and previous periods could be used to predict the future shortage condition.

Future Medicine Shortage Target

The prediction task was formulated as a binary classification problem. A future shortage target was created using the subsequent record of the same medicine and healthcare facility.

The target variable was defined as follows:



Future Shortage = 1: A medicine shortage occurs in the following month.

Future Shortage = 0: A medicine shortage does not occur in the following month.

Thus, the model uses available inventory information to predict whether a medicine shortage will occur one month ahead.

Healthcare Data Variation

Healthcare inventory conditions may vary between districts because healthcare facilities can differ in medicine consumption, stock levels, facility types, and supply conditions. Therefore, district-level variation was considered in the study. Medicine consumption and stockout patterns were analyzed across districts to understand differences in healthcare inventory conditions. This analysis provides a basis for examining whether the learned patterns can be applied to different geographical areas.

Machine Learning Models

Three machine learning classification models were developed for future medicine shortage prediction:

- Random Forest
- Gradient Boosting
- XGBoost

These models were selected as tree-based ensemble learning methods that can handle multiple inventory-related features and classification tasks. The models were trained using the prepared healthcare inventory data.

Cross-District Evaluation

Cross-district evaluation was performed to examine the generalisation of the models across different geographical areas. The data were divided according to districts, with a group of districts used for model training and a separate group of previously unseen districts used for evaluation. The models were trained using the training-district data and subsequently tested on the unseen-district data. The unseen-district evaluation was used to determine whether the models could identify future medicine shortage patterns in districts that were not included during training.

Model Evaluation

The performance of the models is evaluated using Accuracy, Precision, Recall, F1-score, and ROC-AUC.

Accuracy measures the proportion of correctly classified records. Precision measures how many records predicted as shortages were actually shortages. Recall measures how many actual shortage cases were correctly identified. F1-score provides a balance between Precision and Recall. ROC-AUC measures the model's ability to distinguish between shortage and non-shortage cases.

IV. RESULTS AND DISCUSSION

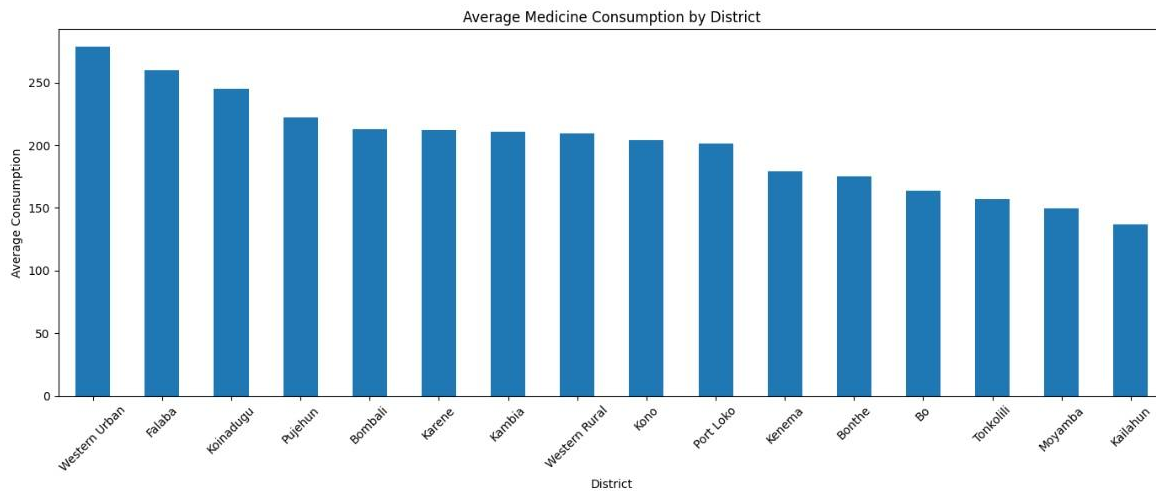
The developed machine learning models were evaluated to determine their ability to predict future medicine shortages using healthcare inventory data. We evaluated Random Forest, Gradient Boosting, and XGBoost using Accuracy, Precision, Recall, F1-score, and ROC-AUC. Two evaluation settings were considered: normal baseline testing and cross-district testing using previously unseen districts.

Healthcare Data Variation Across Districts

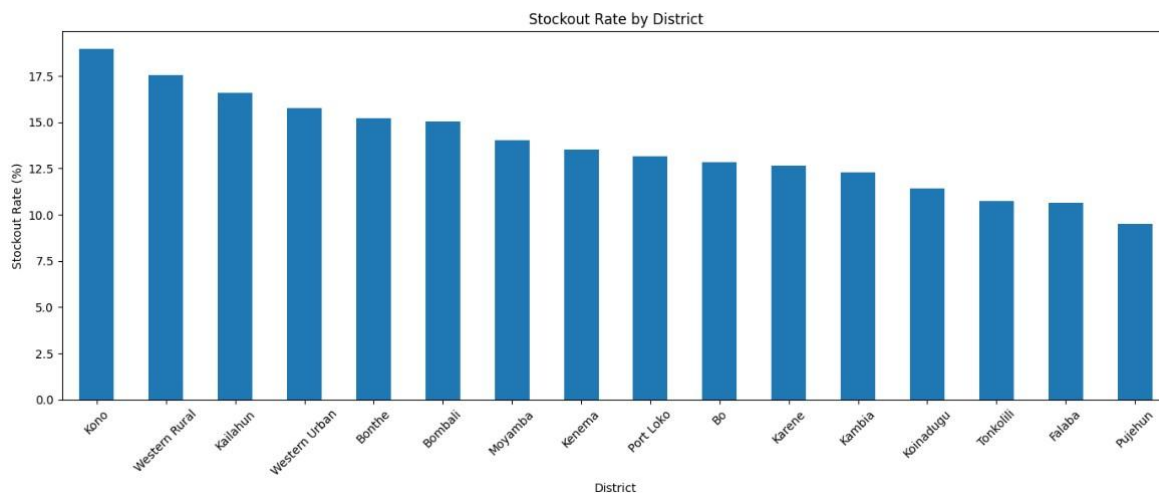
The healthcare inventory data were analysed to identify differences in medicine consumption and stockout patterns across districts. The analysis showed variation in healthcare inventory conditions between districts. Such variation is important because differences in medicine demand, stock levels, and stockout patterns may affect the performance of a shortage prediction model.



Average Medicine Consumption by District



Stockout Rate by District



These district-level variations support the need for evaluating whether the machine learning models can generalise beyond the districts used during training.

Normal Baseline Model Evaluation

In the first evaluation setting, the three machine learning models were evaluated using a normal baseline train-test setup. Accuracy, Precision, Recall, F1-score, and ROC-AUC were calculated for Random Forest, Gradient Boosting, and XGBoost.

The baseline results provide an initial assessment of how the models perform under a conventional testing setting. These results are later compared with the results obtained when the models are tested on previously unseen districts. The comparison helps determine how model performance changes when the geographical area of the testing data differs from the training data.



NORMAL BASELINE RESULTS

	Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
0	Random Forest	0.872396	0.611883	0.200000	0.301464	0.828980
1	Gradient Boosting	0.868558	0.612277	0.123414	0.205422	0.818426
2	XGBoost	0.872785	0.631152	0.182772	0.283459	0.839571

Cross-District Evaluation on Unseen Districts

To examine cross-district generalization, the models were trained using data from the training districts and evaluated on data from previously unseen districts. The same evaluation metrics were used for all three models.

This evaluation provides a more challenging test because the models were required to predict medicine shortage conditions in districts that were not included during training. The results therefore provide information about the ability of the models to generalize to different geographical healthcare settings.

UNSEEN-DISTRICT TESTING RESULTS

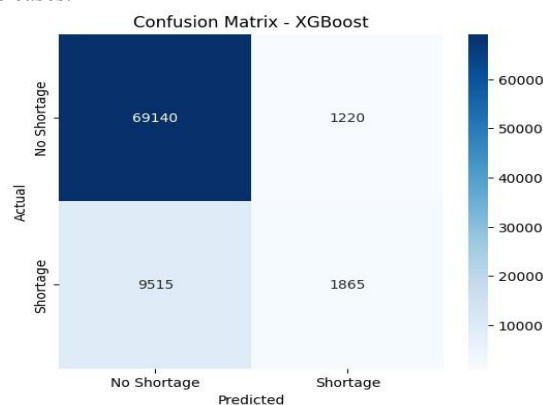
	Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
0	Random Forest	0.865354	0.623841	0.082777	0.146160	0.786215
1	Gradient Boosting	0.866968	0.607203	0.125923	0.208588	0.797040
2	XGBoost	0.868669	0.604538	0.163884	0.257864	0.807336

The unseen-district results were also used to select the final model according to ROCAUC. The model with the highest ROC-AUC on the unseen-district data was selected as the final model for further analysis.

Confusion Matrix of the Final Model

A confusion matrix was generated for the selected final model using the unseen-district test data. It shows the number of correctly and incorrectly classified shortage and non-shortage cases.

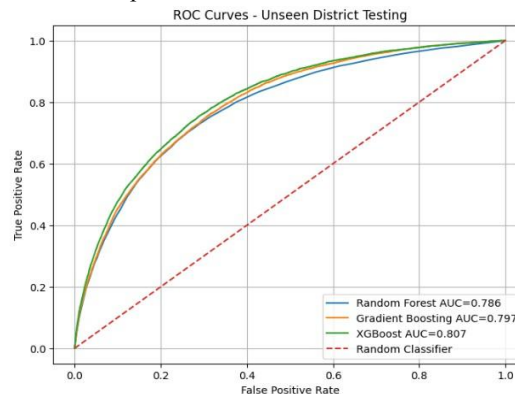
The confusion matrix provides a more detailed view of the model's classification performance, particularly its ability to identify actual medicine shortage cases.



ROC Curve Analysis

ROC curves were used to examine the ability of the three machine learning models to distinguish between future shortage and non-shortage cases. The ROC-AUC value summarizes the model's discrimination performance across different classification thresholds.

The ROC curves for Random Forest, Gradient Boosting, and XGBoost were generated using the unseen-district test data. This analysis provides an additional comparison of the models under the cross-district evaluation setting.



V. DISCUSSION

The results demonstrate the usefulness of machine learning for future medicine shortage prediction using healthcare inventory information. The comparison between normal baseline testing and unseen-district testing provides an understanding of how model performance changes when the models are applied to different geographical healthcare data. The cross-district evaluation is particularly important because healthcare inventory conditions can vary between districts. The results show whether the patterns learned from the training districts can be applied to previously unseen districts. This supports the objective of developing a shortage prediction approach that can be evaluated beyond the geographical areas used during model training.

Limitations

This study has some limitations. First, the study uses healthcare inventory data from Sierra Leone, so the results may not be directly applicable to other countries or healthcare systems with different medicine supply conditions. Second, the final analysis was performed using 25 selected medicine products. Therefore, the results may not represent the shortage patterns of all medicines. The model also focuses on predicting medicine shortages one month ahead and does not consider long-term shortage prediction. Another limitation is that the study uses historical secondary data. The quality and availability of the recorded healthcare information may affect the performance of the machine learning models. Although cross-district testing was performed using previously unseen districts, external validation using data from other countries was not included. Future studies can address these limitations by using a larger number of medicines, longer prediction periods, additional relevant features, and datasets from different healthcare systems.

VI. CONCLUSION

This study developed a machine learning-based approach for predicting future medicine shortages using healthcare inventory data from Sierra Leone. Historical information related to medicines, healthcare facilities, consumption, stock levels, previous stockouts, districts, and time-related features was used to predict whether a shortage would occur in the following month. Three machine learning models, Random Forest, Gradient Boosting, and XGBoost, were developed and evaluated using Accuracy, Precision, Recall, F1-score, and ROC-AUC. The models were tested using normal baseline testing and cross-district testing on previously unseen districts. Among the three models, XGBoost showed the



best performance on the unseen-district evaluation based on ROC-AUC, with a score of 0.8073. This shows that the model was able to identify future shortage patterns even when tested on districts that were not used during training. Overall, the study shows that machine learning can be useful for predicting future medicine shortages and can support better medicine planning and inventory management. Future work can focus on using more medicines, longer prediction periods, additional features, and data from different healthcare systems to improve the model's generalization.

REFERENCES

1. Liu, I., Colmenares, E., Tak, C., Vest, M. H., Clark, H., Oertel, M., & Pappas, A. (2021). Development and validation of a predictive model to predict and manage drug shortages. *American Journal of Health-System Pharmacy*, 78(14), 1309–1316. <https://doi.org/10.1093/ajhp/zxab152>
2. Pall, R., Gauthier, Y., Auer, S., & Mowaswes, W. (2023). Predicting drug shortages using pharmacy data and machine learning. *Health Care Management Science*, 26(3), 395–411. <https://doi.org/10.1007/s10729-022-09627-y>
3. Dong, J., Gao, Y., Liu, Y., & Yang, X. (2023). Development and validation of the nomogram to predict the risk of hospital drug shortages: A prediction model. *PLOS ONE*, 18(4), e0284528. <https://doi.org/10.1371/journal.pone.0284528>
4. Joshi, S. V., Patil, S. B., Patil, S. N., Bhosle, S., Karhadkar, N. P., & Rathore, Y. K. (2025). Machine learning applications in hospital pharmacy for predicting drug shortages and supply chain optimization. *Research Journal of Pharmacy and Technology*, 18(6), 2939–2945. <https://doi.org/10.52711/0974-360X.2025.00393>
5. Park, S. M., Lee, S. H., & Lee, J. H. (2025). Drug shortage in South Korea: Machine learning-based prediction models and analysis of duration and causal factors. *Frontiers in Pharmacology*. <https://doi.org/10.3389/fphar.2025.1608843>
6. Angula, T. N., & Dongo, A. (2024). Assessing the impact of artificial intelligence and machine learning on forecasting medication demand and supply in public pharmaceutical systems: A systematic review. *GSC Biological and Pharmaceutical Sciences*, 26(2), 140–150. <https://doi.org/10.30574/gscbps.2024.26.2.0071>
7. Agada, A. V. (2024). Predicting the pharmaceutical needs of hospitals. *International Journal of Public Health, Pharmacy and Pharmacology*, 9(1), 1–13. <https://doi.org/10.37745/ijphpp.2013/vol9n1113>

