Predicting medical drug sales in a specific area for categorical drugs using time series forecasting

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***Abstract*— Accurately forecasting pharmaceutical drug sales is a significant challenge faced by many firms, particularly in Sri Lanka, where factors such as seasonality, weather, local health crises, importation issues, currency fluctuations, and economic instability affect inventory management. These challenges often lead to frequent conditions of either shortages or overstocking of drugs, which adversely affect healthcare delivery and business profitability. This study addresses this issue through the development of a data-driven system using machine learning to predict drug sales efficiently and accurately. This work involved gathering sales data from local pharmacies, performing some pre-processing steps, and implementing a time-series forecast using the SARIMA model, which works efficiently with seasonal variations in sales data. A locally hosted, user-friendly web application was developed using the Flask framework to present these predictions in a readable format for pharmacists and drug sellers. The system was also validated on an external dataset, demonstrating high accuracy in the forecasted sales, which helped improve inventory management practices. The proposed system reduces drug shortages, minimizes wastage due to expiration, and enhances supply chain efficiency, thereby improving healthcare delivery and business outcomes. This research provides evidence of the opportunity to leverage pharmaceutical sales data to identify disease trends and inform public health strategies. The model can be further improved and applied in various aspects by including additional variables. This research bridges gaps in supply chain management, improving the availability of medications and making inventory management more predictable, benefiting both public health and industry stakeholders.**

Keywords—drug sales analysis, pharmaceutical sales prediction, public health, SARIMA, time series forecasting

I. Introduction

The pharmaceutical industry is inherently dynamic; hence, accurate sales forecasting is increasingly crucial for public health and for responding with appropriate marketing strategies. The industry in Sri Lanka faces many challenges, including seasonal business cycles, varied weather conditions, local epidemics, importation obstacles, exchange rate fluctuations, and economic instability. These factors contribute to unpredictable demand for drugs, often resulting in drug shortages and oversupply, which negatively impact public health outcomes and business viability. Despite the critical importance of accurate sales predictions, predictive modeling techniques have been underexplored in the Sri Lankan pharmaceutical market.

This study addresses these challenges by developing a data-driven system that leverages advanced machine learning algorithms to forecast drug sales with high accuracy, particularly focusing on categorical drugs. The research analyses historical sales data to identify important patterns and trends driving drug demand, enabling better decision-making in inventory and supply chain management for sellers and pharmacists. A user-friendly web application, built using the Flask framework, visually presents sales forecasts in an understandable format for practical implementation of the real-world problem. The models are subjected to external validation with datasets, ensuring their reliability and applicability. This work concludes by bridging the gap between data science and pharmaceutical retailing in Sri Lanka, enhancing drug availability and reducing wastage to improve efficiency in the supply chain and, as a result, contribute to a healthier and more resilient society.

II. Literature Review

According to the U.M. Sirisha, M.C Belavagi, G. Attigeri [23], Time series forecasting using historical data is significantly important nowadays in many fields including healthcare field. Profit analysis using financial data is crucial for any type of businesses and companies. It helps to find the predict values for the future and get benefits for the business thorough it and, if a time series is univariate and contains trend or seasonal components, then can use Seasonal ARIMA (SARIMA) model. K. Alice, S. H. ul Haq Andrabi, and S. Jha said that [22], Sales forecasting is the process of predicting future sales for a given time. It is an important business function that helps companies to make correct decisions about future plans. Sales forecasting need for businesses to plan, budget, invest and to get profits. More accurate sales predictions can help to make better-informed business decisions.

A. *Traditional Forecasting Methods in Pharmaceutical Sales*

- Naive Bayes: Known for simplicity and effectiveness but assumes predictor independence, limiting its accuracy in complex sales dynamics [1]
- Seasonal Naive: Utilizes sales data from equivalent past intervals to capture seasonal trends effectively [2]

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- ARIMA: Effective for linear patterns, but combining it with other methods improves performance in non-linear scenarios [3]

- Exponential Smoothing: Includes Single, Double, and Triple (Holt-Winters) methods for steady trends and seasonality, but struggles with nonlinear data [4]

B. Machine learning techniques for pharmaceutical sales forecasting

- Neural Networks (LSTM): Bandara [8] highlights the capabilities of LSTM networks in effectively remembering and retrieving information over extended periods, making them well-suited for forecasting tasks. In a study by Yuxuan Han [11], LSTM models outperformed traditional methods like ARIMA in forecasting pharmaceutical sales, demonstrating their ability to capture complex data patterns over time. The study emphasizes the potential of LSTM networks to significantly improve sales forecasting accuracy in the pharmaceutical industry.

- Ensemble Methods (XGBoost) Chen and Guestrin [10] introduce XGBoost, highlighting its ability to handle sparse data, perform parallel computing, and find optimal tree splits using both exact and approximate algorithms. In the context of pharmaceutical sales forecasting, XGBoost has demonstrated its effectiveness in capturing complex non-linear patterns and handling high-dimensional data, making it a valuable tool for accurate predictions.

- Prophet: Zunic et al. [7] highlight Prophet's ability to capture intricate sales patterns, making it well suited for applications in the pharmaceutical industry, where seasonality plays a significant role, and it is a powerful forecasting tool designed to handle complex patterns ranging from daily to yearly seasonality.

C. Advantages over Traditional Methods

- Non-linear Pattern Capture: These techniques can effectively capture non-linear relationships and complex patterns in data, which are common in pharmaceutical sales dynamics [9]

- Handling High-Dimensional Data: Ensemble methods like XGBoost can handle high dimensional data with ease, making them suitable for forecasting tasks involving multiple predictors [10]

- Adaptability: Neural networks and ensemble models can adapt to changing market conditions and learn from new data, providing more accurate and uptodate forecasts [8, 9]

- Seasonality Modelling: Techniques like Prophet are specifically designed to handle multiple seasonalities, which are crucial in pharmaceutical sales forecasting [7]

D. Challenges Faced in the Pharmaceutical Supply Chain and Forecasting

Moosivand, Rajabzadeh Ghatari, and Rasekh [13] explore the challenges of forecasting and supply chain planning in pharmaceutical manufacturing. They identify several key challenges including.

- *Demand variability:* The demand for pharmaceutical products can be highly variable and unpredictable, influenced by factors such as market trends, disease outbreaks, and changes in healthcare regulations.

- *Regulatory compliance:* The pharmaceutical industry is heavily regulated, and companies must comply with strict guidelines and regulations regarding drug manufacturing, storage, and distribution, which can add complexity to supply chain operations.

- *Coordination:* Effective coordination between different stages of the supply chain, such as manufacturing, distribution, and retail, is crucial for ensuring timely delivery and avoiding shortages or oversupply.

Yani and Aamer [14] focus specifically on the importance of demand forecasting accuracy in the pharmaceutical supply chain. They highlight that inaccurate demand forecasts can lead to significant consequences, such as stockouts, expired inventory, and inefficient resource allocation. The authors suggest that machine learning techniques can improve demand forecasting accuracy by capturing complex patterns and incorporating multiple data sources.

Zhu et al. [15] propose a novel demand forecasting framework for the pharmaceutical industry that leverages advanced machine learning models. They emphasize the need for accurate forecasting to address the challenges of demand variability and supply chain complexity. The framework integrates multiple data sources, including sales data, inventory levels, and external factors like weather and disease patterns, to provide more reliable demand predictions. The BioPhorum Operations Group's Best Practice Guide [12] underscores the necessity of accurate forecasting, transparent communication, and strategic alignment in improving supply chain efficiency within the biopharmaceutical industry. The guide highlights the importance of forecasting in ensuring consistent patient supply and effectively responding to dynamic market demands.

KPMG's "Pharma 2030: From evolution to revolution" report [17] further emphasizes the potential of artificial intelligence (AI) and big data analytics in enhancing demand forecasting accuracy and resource allocation efficiency within the pharmaceutical industry. The report suggests that these technologies will revolutionize traditional practices and enable more data-driven decision-making in supply chain management.

III. Design and Implementation Methodology

In this section, a systematic approach is described for designing and implementing the predictive system for medical drug sales forecasting in particular areas. The approach assures the development of a useful and easy to use solution, mixing machine learning techniques and a web-based interface to help pharmacists and drug sellers manage inventory.

Following diagram outlines the structured process followed in this research, from identifying the problem and objectives to data collection, analysis, model development, and the final presentation of findings and recommendations.

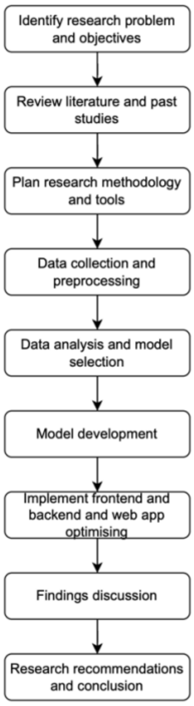

Fig. 1. Research flow diagram

The overall design is modular in nature comprising of the data collection, data preprocessing, development of the machine learning model and integration with web application. The aim is to enable smooth linkage between this predictive model and end users by supplying access through a web interface and preserve accuracy and reliability of sales forecast [13] and [15].

A. Data Collection and Preprocessing

The data of sales was compiled with the help of returned registered subordinate local pharmacies. One-year data was deemed a necessary palette to infer seasonal trends and variations periodically, where the forecasting model is sensitive to those variations [14] and [18].

Again, the actions that were taken on this data set can be well understood under the broader umbrella of preprocessing of data. Data pre-processing involved dealing with missing values and outliers with a view on achieving clean data [5]. Feature engineering was performed by categorizing the dataset by drug types and including time-dependent factors that may affect sales, including weekly sales [6]. For finding the stationarity of the time series data the first integrated stationary test was performed with the help of Augmented Dickey–Fuller (ADF) test [5]. Also, the data was divided into training and testing data sets in order to feed into a machine learning model used to predict performances from the obtained information.

B. Model Development

The Seasonal Autoregressive Integrated Moving Average (SARIMA) model was selected for its robustness in handling seasonal patterns and trends in time series data. This made it well-suited for predicting the sales of medical drugs across different categories [8],[3] and [21]. The SARIMA model was trained on historical sales data for each drug category, with parameters optimized to minimize prediction error during training. The model outputs weekly sales forecasts, including confidence intervals that indicate the reliability of the predictions [21].

C. Web Application Development

Essential to the current design, Flask was used to connect the backend predictive model to the frontend look and feel. This allowed for a proper linkage between the actual machine learning model and the final web application, thereby allowing the predictions of the model to be passed on to the user in real time with an easy to use web interface [7] and [12].

1)Frontend Development: This web site has been implemented using HTML and CSS to present a flawless, consistent and user-friendly interface. C B devices were standard dialog boxes which were used for selection of drug category and prediction date and results of drug prices were given numerically and in graphical form for better interaction and for better understanding of results [10] and [12].

2)Backend Development: Most importantly Python was very useful in handling of back end of logic to interconnect the web base interface and the machine learnt model. By employing Flask's Render Template, HTML page inputs were entered by the user and directly translated to page generation, eliminating complications inherent in the interaction process and offering a smooth user interface [7] and [19].

D. User Interface Design

Simplicity and functionality in design made user interface (UI) design for a usable user interface for users, which include pharmacists and drug sellers. Usability, readability and navigation were key design elements implemented.

1)Pages: The web application includes four primary pages to facilitate user interaction. Navigation is from input to results and/or from results to about and from start page as the entry point. The Input Page has a form based interface where we can select which mature drug category to predict and what date to predict. The output on the Results Page shows the predicted sales values, the confidence intervals and an comparative line graph between the historical and forecasted data. And the About page provides the details of the why, what, who, and how of the application and the development team behind this project [15] and [16].

Fig. 2. Application starting page

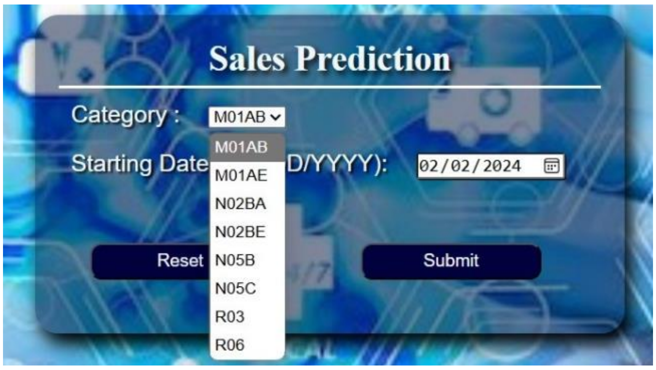

Fig. 3. Category selection page

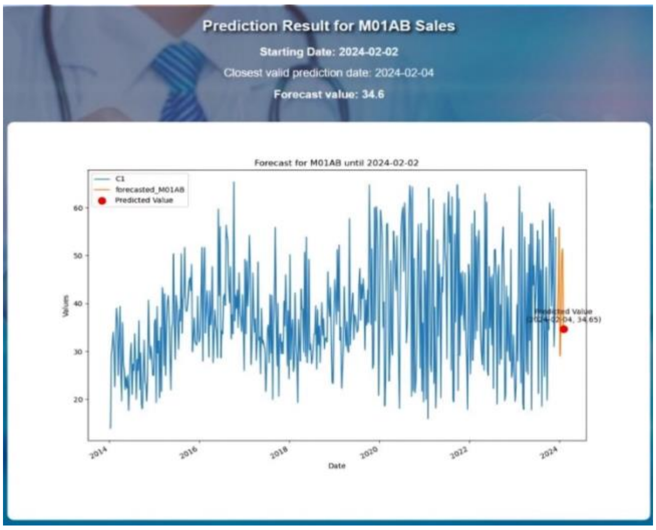

Fig. 4. Showing final prediction

2)Form Elements: It also features user friendly form controls to make using it simple. Users can choose a specific date for the sales forecast with the Date Picker and easily select drug categories in the Dropdown Menus grouped under its related classifications. Desired results page was crafted to deliver the forecasts. Using Line Graphs, we can see predict sales trends against historical data so that our viewers can understand the data in clear and easy ways. Graphs show labels, legends, different colors separately for historical and predicted data points for comparing. Furthermore, Dynamic Visualization updates in real time based on user input providing immediate feedback [9].

3)Visualization: Key principles for an optimal user experience guide the design. To create a look that's professional but easy to understand, a medical themed, high contrast, low demand interface was chosen. Readability: Being white text on dark background, with the typography making it really clear and legible to read. Responsiveness: It's fully compatible with desktops, tablets and mobile phones, so a user experience across platforms is no issue [12][19].

4)Consistency and Aesthetics: The design adheres to the following principles

- Color Scheme: a medical-themed, high contrast, low demand, low resource interface with elements that promote a professional and easy to understand interface.
- Readability: White text on dark backgrounds for easy reading, a clear and legible typography. Responsiveness: Compatible with all devices, desktops, tablets and mobile phones [12].

5)Accessibility Features: The design is designed for ease of use and caters for a wide range of users, from members with no technical experience at all. It styles buttons and links with hover effect hover effects and tooltips for guidance. Navigation is intuitive, and users can literally switch from one page to another, and if it's not clear already, there is a workflow and users who lack tech skills still got access [20][19].

6)Implementation Workflow: Python was used to develop the backend of the application. It uses libraries from NumPy and Pandas to clean the data in the most efficient way possible. We also used these libraries to clean and structure data and handle large datasets [6][18]. After analyzing forecasting capabilities via scikit-learn, an algorithm was chosen to induce SARIMA model which can handle seasonal patterns and trends and can generate accurate and reliable forecasts [8][3]. Robust error handling and data validation was added for maintaining the predictions' quality, as well as for the backend.

This was created making use of HTML and CSS, to give an appealing, wearable, and responsive structure. A consistent user experience across devices, from desktop to mobile phone, was taken care of. Interactive elements were introduced to increase the visibility and provide real time understanding to users. These features keep users in place, no matter the expertise in terms of the app.

Flask served as a lightweight Python web framework with the integration implemented between the front end and back end. It bridged real time communication between the prediction engine and the user interface. The backend processed user inputs (e.g. selected drug categories, and dates) and returned required predictions to the frontend in a user friendly way. This integration made the system both functional and user friendly, it became a great experience for mouth to mouth sales for pharmacists and for drug sellers [19][7].

7)Diagrams Supporting Design: Diagrams of the key aspects of the design and user interactions were developed to effectively communicate how the system works and its workflow. Through these diagrams, these describe how the system behaves, who are the users and what are the process to be done in order.

7.1) Use Case Diagram: The Use Case Diagram shows a typical scenario between the users—pharmacists and administrators—and the system. The pharmacists interact with the application by inputting for drug categories and forecast dates, viewing of predictions and utilizing the results for inventory management. In fact, experts who maintain the system include administrators who update datasets, uphold the functioning of the prediction model, and fix technical problems [12]. A key functionality diagram has been given which shows key functionalities such as data input, result retrieval, and system management and illustrates how different user roles participate in working of the system. Use case diagram provides a visual view of the interactions, which also gets us the idea about the use of the application and the involvement of the users [16].

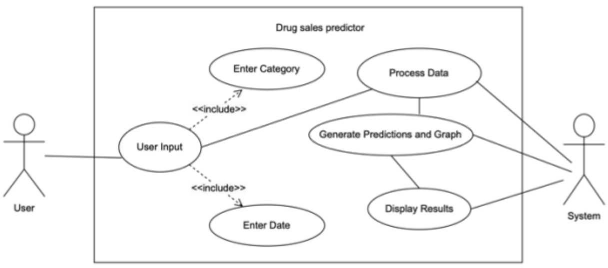

Fig. 5. Use case diagram

7.2) Activity Diagram: This Activity Diagram represents the sequential flow of actions within the system, from system input to system display. Then we start with users inputting the data (right), which includes drug category and prediction date. Then, the backend processes this data and then generates predictions through the use of the SARIMA model. This output is then validated and processed by the system, and results are then displayed on the user interface as long as they met the accuracy thresholds [8]. Decision points are also captured in the diagram, such as whether the input data is valid, and it outlines when an error handling needs to take place. This whole representation of activities guarantees the system design to be clear enough on how all its activities work, thus making it easy to debug, change or scale the application in the future [5].

Fig. 6. Activity diagram

Together, these diagrams give a clear and structured picture of the design of the system: including the details of how the technical elements work together, and also how user-centric functions support the system's goals.

IV. Discussion

In this project Our aim is to create a locally host website for a pharmacy of an area to predict medical drug sales in that area for categorical drugs. Through this project we basically give the output as predicted sales for a chosen drug category for a given date. And visualize the historical sales and forecasted sales up until the input date by a plot. For this whole project we went through several processes.

1)Find a data set: We spend more time to find an actual data set. As a result of it We finally found an actual pharmacy data set. So, this leads us to a real-world application. Data pre-processing at this point we had to do remake the data set according to our project. We had to categorize data under eight categories, handle missing values and remove outliers. We got a structured data set which allows for meaningful forecasting. Then we did a stationarity check, we used the Augmented Dickey-Fuller (ADF) test to check stationarity in the sales data.

In our case it was non-stationary because we found that p-value is 1. Then we used differencing to make it stationary because stationarity is crucial for time series models like SARIMA.

2)Model selection and fitting: We chose Seasonal Autoregressive Integrated Moving Average (SARIMA) model with the parameters that we got through the previous tests. The SARIMA model was fit to the historical sales data for each medical drug category. The fitting process involved optimizing parameters to minimize prediction error. Our model forecasts future sales for a particular category weekly, including point forecasts (predicted mean). Finally, we created an accurate model.

3)Frontend development: We created a user interface which is a user-friendly and attractive web front end for our project using HTML, CSS. The user should give the category and date, then the prediction value and a user-friendly plot shows in UI as the output.

4)Backend development: Python flask API is the backend of our project which handles the communication between front end and the prediction model successfully.

5)Significance of this study: This study plays a crucial role in improving pharmaceutical sales forecasting, particularly in Sri Lanka, where such applications remain underexplored. By leveraging the SARIMA model, the research enhances accuracy in predicting drug demand, helping to minimize shortages and overstocking.

The integration of machine learning with inventory management optimizes supply chain efficiency, reducing costs and ensuring better availability of essential medications. This contributes to the advancement of AI-driven decision-making in healthcare logistics.

6)Identified limitations: The limitations of the research include data availability and quality, as the accuracy of predictions relies on the availability and reliability of historical sales data, with missing or inconsistent data potentially affecting model performance. Additionally, the model does not account for external factors such as economic conditions, policy changes, or sudden health crises that could impact drug sales. The study's regional specificity also limits its generalizability to other areas with different market dynamics. Furthermore, more sophisticated models may require significant computational power, which could pose challenges for real-time forecasting in resource-constrained environments.

Furthermore, the study's findings can serve as a foundation for future research, encouraging the adoption of more advanced AI models like LSTM and XGBoost for improved forecasting accuracy.

V. CONCLUSION

Interpret prediction sales values of medical drug categories for future dates is the main result of our project. And we used SARIMA to build our model, the SARIMA model demonstrated robustness in capturing seasonal patterns and trends in the sales data, providing reliable forecasts that can be trusted by pharmacies for decision making. And our model built up as a weekly prediction model. As a result, we can see the mean prediction value for the week that your input date in. We build up this model by targeting a pharmacy. So, user can decide the number of drugs for each category that they need for a date or a week, therefore the pharmacy can identify most needed medical drugs for a particular time for their area. Because of that they get a higher profit from reducing the drug shortage and drug wastage.

In the other hand patients can buy medicines when they need it, this helps to make a healthiness society. The results of our project will give benefits for manufacturing companies of medical drugs to reduce drug wastage save their money as well as for the government to import medical drugs according to the demand by expanding this application over the country.

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