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Forecasting Drug Demand for Optimal Medical Inventory Management: A Data-Driven Approach with Advanced Machine Learning Techniques

Vibin Ravi Kumar[1]
Research Associate,
Innodatatics, Hyderabad, India

Pallavi Waghmare[2]
Mentor,
Research and Development,
Innodatatics, Hyderabad, India

Sampath Bukya[3]
Team Leader,
Research and Development,
Innodatatics, Hyderabad, India

*Bharani Kumar Depuru[4]
Director, Innodatatics, Hyderabad, India
OCR ID: 0009-0003-4338-8914

Dr. Ilankumaran Kaliamoorthy[5]
CEO, Rela Institute and Medical Centre,
Chennai, Tamil Nadu, India

Corresponding Author: *Bharani Kumar Depuru[4]

Abstract:- **A hospital's capacity to allocate resources efficiently and guarantee drug supply depends on effective medical inventory management. This study paper offers a thorough data-driven strategy for drug demand forecasting that makes use of cutting-edge machine learning methods, intending to improve medical inventory management procedures. A range of machine learning algorithms were used to precisely model and anticipate drug demand trends using historical data, including Deep Learning-based models, time series forecasting techniques, and ensemble learning methods. To determine the best strategy for predicting drug demand, the study compares the performance of various algorithms.**

Healthcare facilities can improve patient care, reduce waste, and achieve optimal supply chain performance by minimising stockouts, lowering surplus inventory, and optimising the supply chain. The findings of this study increase medical inventory management procedures by offering insightful information on the use of cutting-edge machine learning methods for precise drug demand forecasting. In turn, this promotes the use of evidence-based decision-making and medical resources. Machine learning for forecasting has enormous potential for revealing previously unknown patterns in disease, treatment, and care as the healthcare sector experiences a data revolution with the growing use of Artificial Intelligence (AI), Predictive Analytics, and Business Intelligence. The research intends to enhance people's health outcomes, socioeconomic status, and day-to-day activities by resolving the difficulties caused by the complexity of pharmaceuticals and ensuring the supply of vital medications.

The supply of essential drugs and life-saving supplies can be less uncertain with accurate demand estimates, which helps to create a well-organised and effective health supply chain. The study highlights the significance of using suitable prediction models, such as collaborative predictions based on end-user consumption data, economic order quantity, or the Min/Max formula, to ascertain the necessary dosages of critical medications while taking into account available resources, supply chain information, and inventory levels. Healthcare organisations can considerably reduce prediction errors and improve the efficiency of medical inventory management by utilising the results of this extensive research.

Keywords: *- Drug Demand Forecasting, Machine Learning in Medicine, Medical Inventory Management, Healthcare Supply Chain, Predictive Analysis, Hospital Management*

I. INTRODUCTION

The key objective of this study is to improve drug demand prediction accuracy through the use of data-driven strategies and cutting-edge machine-learning techniques. The research attempts to analyse historical medication sales data and identify significant patterns and trends using RNN (Recurrent Neural Network), BI RNN (Bidirectional Recurrent Neural Network), LSTM (Long Short-Term Memory), BiLSTM (Bidirectional Long Short-Term Memory), GRU (Gated Recurrent Unit), BiGRU (Bidirectional Gated Recurrent Unit), and Ensemble models (Gradient Boost). These models have the potential to increase the accuracy and dependability of medication demand forecasting since they are built to handle sequential data and capture dependencies over time. By assessing the efficiency of these cutting-edge machine-learning algorithms in predicting drug demand and improving medical inventory management.

India's pharmaceutical industry, which mostly depends on China for the supply of some key chemicals and intermediates, has been constantly watched to assess the impact of Covid-19 on its supply chain. At the time, Covid-

19 was in charge of numerous ground-breaking innovations in pharmacy material management. Lack of information regarding the spread of Covid-19 and lack of visibility over the delivery of some bulk medications causes speculative price hikes [8].

Also, drugs have always been a vital component of both curative and preventive healthcare. A country's entire public health budget, which ranges from 40 to 60 percent, is spent on purchasing medications. Building a capable procurement system is the only option to increase the majority of the population's access to medications while staying within the constraints of the available budget [9].

Forecasting drug demand accurately is crucial for managing healthcare systems. It makes it possible for healthcare providers and organisations to maximise their inventory, lessen stockouts, and prevent drug overstock. Healthcare institutions may streamline operations, improve patient outcomes, and ensure the timely availability of important medications by comprehending and forecasting future drug demand. Accurate demand forecasting also aids in cost control, waste reduction, and supply chain logistics optimization.

The outcomes of this study could be advantageous to several stakeholders in the healthcare ecosystem. The findings can be used by hospitals, pharmacies, and healthcare organisations to streamline their drug procurement processes, cut costs, and guarantee the availability of critical pharmaceuticals. The insights can be used by pharmaceutical makers and companies to streamline inventory management, distribution, and production. In the end, greater drug demand forecasting will help patients and the healthcare system as a whole by enhancing patient care, reducing pharmaceutical shortages, and better-allocating resources. The optimization of medical inventory management has grown in relevance as computer systems have advanced, emphasising the necessity of our research in this area.

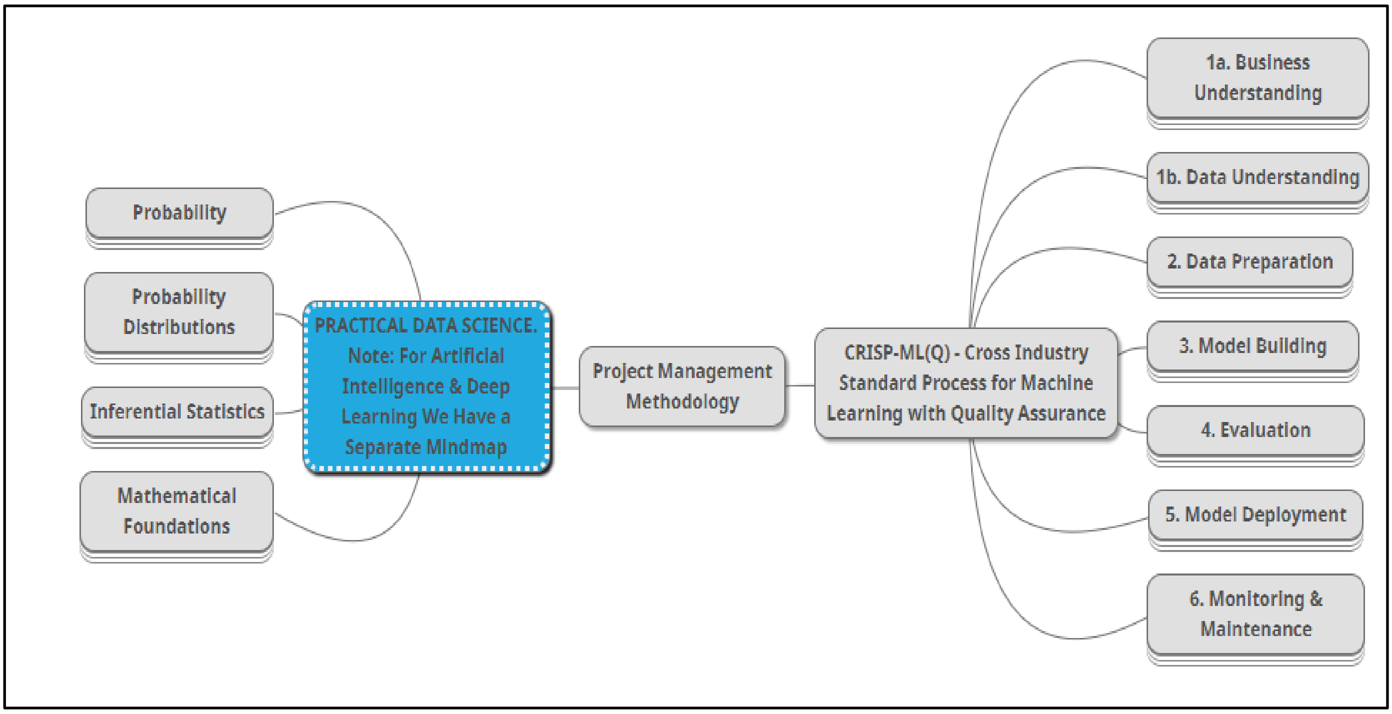

Fig 1 This Figure Depicts the CRISP-ML(Q) Architecture that We have followed for this Research Study.
(Source: Mind Map - 360DigiTMG)

To progress with this study in a structured manner we have utilised and followed the CRISP-ML(Q) (CRoss-Industry Standard Process model for the development of Machine Learning applications with Quality assurance methodology) Mindmap (ak.1) [Fig.1]. Understanding the goals and needs of the healthcare sector concerning the forecasting of drug demand and the management of medical inventory is part of the first step, referred to as "Business Understanding" [Fig.1]. We aimed to deal with issues like stockouts, excess inventory, and inefficient resource allocation that healthcare providers encounter. Healthcare providers may optimise their inventory levels, cut expenses, and guarantee that patients have timely access to pharmaceuticals by correctly forecasting drug demand.

To better understand the factors impacting drug demand, we have gathered and analysed pertinent data sets during the “Data Understanding” [Fig.1] phase. Data from the past on patient demographics, disease prevalence, and other contextual factors are also included. To build the groundwork for further modelling stages, exploratory data analysis techniques are used to find patterns, correlations, and outliers within the data.

Pre-processing the gathered data to verify its integrity and usefulness for modelling is known as “Data preparation” [Fig.1]. The data must be cleaned, missing values must be handled, and any necessary variable transformations must be made. Techniques for feature engineering can be used to extract useful predictors and improve the models' capacity for prediction.

“Data mining” [Fig.1] is the study of gathering, cleaning, processing, analysing, and deriving practical insights from data. To put it another way, data mining is the practice of looking for patterns in datasets that contain a lot of data (big data) to uncover undiscovered information or knowledge. This is done by extracting and examining significant or interesting patterns from data stored in databases [11].

The power of cutting-edge machine-learning approaches is revealed during the “Model Building” [Fig.1] stage. To create a reliable and precise forecasting model, we use a variety of algorithms, such as ensemble approaches and deep learning Models. These methods are excellent at identifying intricate connections and trends within the data, allowing us to produce accurate and trustworthy predictions of the demand for drugs.

The generated model is then linked to the medical inventory management system during the “Model Deployment” [Fig.1], allowing for real-time forecasting and optimization of drug inventory levels. To enhance their supply chain management and resource allocation strategies, healthcare practitioners, policymakers, and pharmaceutical corporations can use the research findings as practical guidance.

The CRISP-ML(Q) is one of the standards used in data mining. Because CRISP-ML(Q) is most frequently used in data mining development, business problem analysis, and data mining projects, Mariscal, Marba, and Fernandez [12] declared it to be the de facto standard for the creation of data mining and knowledge discovery projects [3].

➢ *Architecture Diagram*

Before going deeper into possible issues, we would like to have an analogy to an English idiom that says "A picture is worth a thousand words". As per this wiki explanation, "it refers to the notion that a complex idea can be conveyed with just a single still image or that an image of a subject conveys its meaning or essence more effectively than a description does"

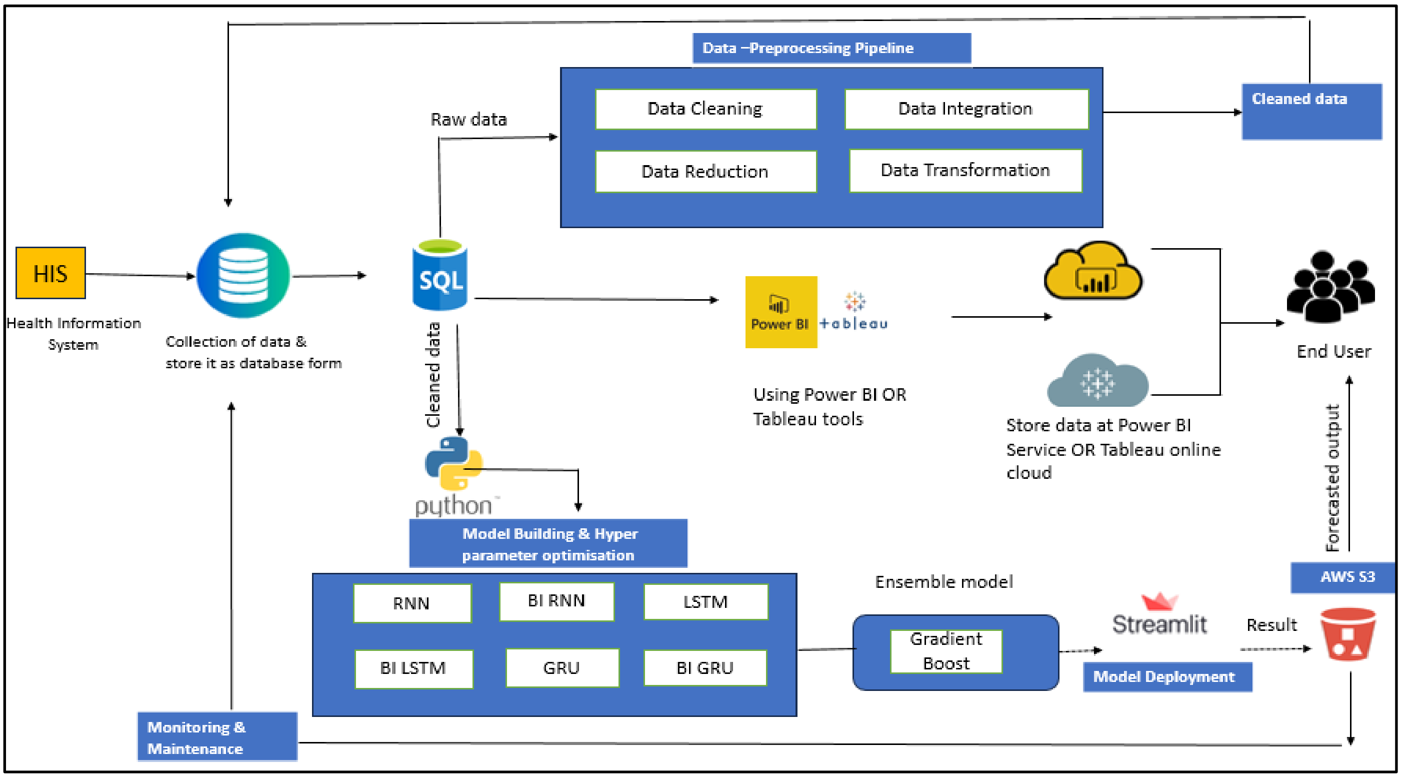

Fig 2 Architecture Diagram Representing a Drug Demand for Optimal Medical Inventory Management Incorporating Forecasting Models

Data Collection from the medical inventory system [Fig.2, 3] is the first step in the process of acquiring details on inventory, sales, and other pertinent information. A SQL (Structured Query Language) is then used to store and retrieve the obtained data effectively. Next, Data Pre-processing [Fig.2, 3] is applied, which includes data integration to combine data from different sources, Data Reduction [Fig.2, 3] is used to pick out key features, Data Cleaning [Fig.2, 3] is used to deal with missing values and errors, and Data Transformation [Fig.2, 3] is used to guarantee the consistency and quality of the data.

After pre-processing, exploratory data analysis (EDA) is carried out to discover patterns, comprehend the data's characteristics, and obtain new insights. To analyse sequential patterns and identify temporal correlations, machine learning models like RNN, BI RNN, LSTM, and Ensemble model (Gradient Boost) [Fig. 2, 3] are trained on the pre-processed data after EDA. We decide on the ensemble model because it provides the highest accuracy among these models.

Using Streamlit [Fig.2, 3], a web application framework that enables the development of interactive interfaces for visualising and engaging with the models, the trained models are then deployed for use in real-time. The deployed models are kept in an AWS S3 bucket [Fig. 2, 3], making it simple for other systems or users to access and use the model artefacts.

The deployed models and the entire system are always being watched over to guarantee continued performance and correctness. This entails monitoring model metrics, doing quality assurance checks on the data, and releasing timely updates as soon as new data becomes accessible or as business requirements alter.

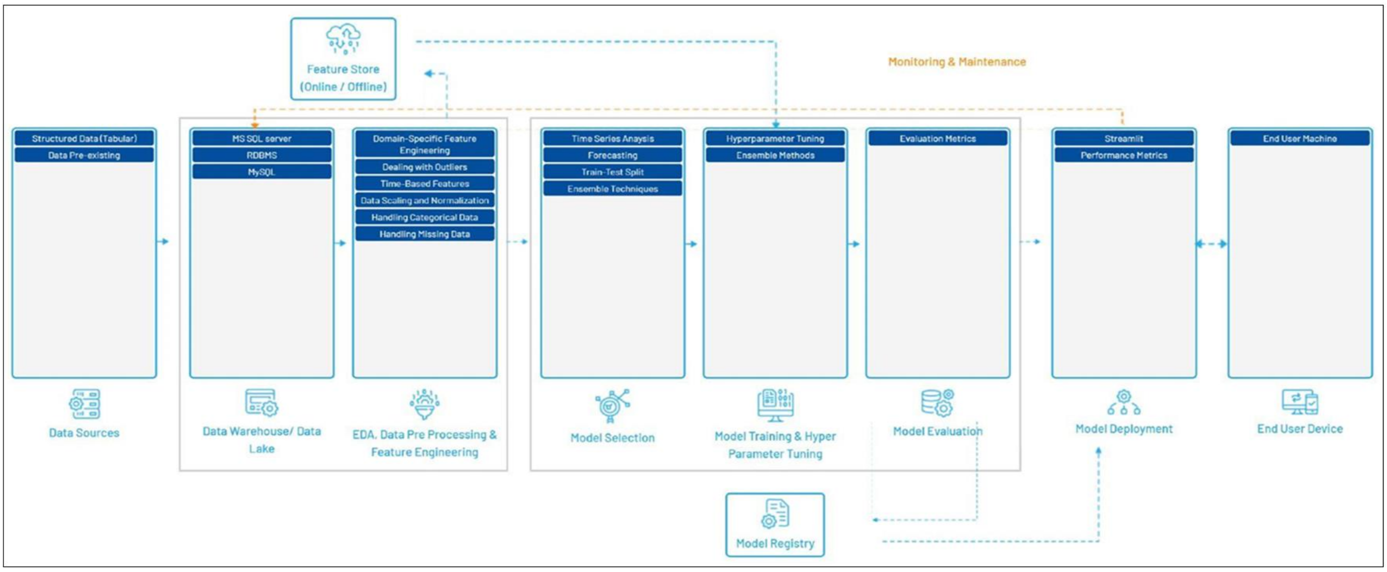

Fig 3 This Machine Learning Architecture Diagram Illustrates the Stages Involved in Achieving Optimal Medical Inventory Management by Forecasting Drug Demand.
(Source: Open-Source ML Workflow Tool- 360DigiTMG) (ak.2)

II. METHODOLOGY AND TECHNIQUES

A. Data Collection

Using the hospital's Health Information system (HIS), a 4-year dataset for this Research was gathered. The dataset included drug sales information gathered over four years, giving a complete picture of the hospital's medicine supply.

Data has been utilised and suitably processed for the prediction process. Predicting future data that can be used in the healthcare supply chain is, in this regard, one of the most important objectives of time series analysis.

For this work, health supply chain management data were employed. They featured information on consumption, inventory, orders and reorders, and purchasing prices [1].

The dataset covered a wide range of medications and the sales records for them, gathering details such as drug category, volumes, and sales dates. The medicine categories, such as injections, tablets, fluids, and more, were explained by the subcategory feature. While the date of the sale provided the precise day the drug was sold, the quantity feature stated how much of each drug was purchased.

The historical records from the HIS that were used in this study's dataset covered a sizable 4-year time range. This larger time frame made it easier to explore trends and patterns over a longer period and allowed for a thorough investigation of the pharmaceutical inventory.

The initial shape of the dataset was (5643260, 23), reflecting the considerable number of records and features included in the analysis.

The study provides a summary of the number of drugs consumed for both the train and test sets. The train set included 39 months of data and the test set included 12 months of observations [1].

B. Data Pre-processing

For this report, information on medical inventory management from 4+ years was gathered. They featured information on consumption, inventory, orders and reorders, and purchasing prices.

Before analysis, the dataset underwent Data Cleaning [Fig.2, 3] and Exploratory Data Analysis (EDA) [Fig.1] to uncover insights relevant to forecasting. Specifically, the data considered for the analysis were limited to the date of drug purchase and the subcategory of drugs. The subcategory feature includes a total of 17 categories encompassing 2,470 individual drugs.

We don't go with total counts, consequently, the reason why we use the method below.

To select the drugs for forecasting, a weighted approach was employed. This technique involved calculating the weightage of each drug based on its cost and quantity. The cost weightage was computed as the product of the medicine cost and the quantity purchased, divided by the total cost of all drugs in the inventory. Similarly, the quantity weightage was calculated as the ratio of the quantity purchased for each drug to the total quantity of all drugs. The total weightage of each drug was obtained by combining the cost weightage and the quantity weightage.

Let us provide a comprehensive analysis of the Exploratory Data Analysis (EDA) [Fig.2, 3] research findings:

EDA is an evaluation method that uses data to uncover designs, solve issues, and test hypotheses using analytical and visual representations. EDA is carried out using data sets [9]. EDA on data collection allows us to continuously learn new perceptions. In this work, we used specific analytical techniques on the HIS pre-processed data set [14].

C. Variables and Measures

The variables used in this study include 23 among those important variables are subcategory, quantity, and sales date. The subcategory represents the category to which each drug belongs. The quantity denotes the number of drugs purchased. The sales date indicates the date when the drug was sold.

D. Statistical Analysis

The statistical analysis primarily involved descriptive statistics to summarise the dataset and Pareto analysis to identify the drugs contributing to a significant portion of the sales, cost, and profit.

The examination of the distribution of drug demand benefits greatly from the addition of a Pareto chart. Based on the Pareto principle or 80/20 rule, the Pareto chart graphically illustrates the total percentage of drug demand attributable to various categories or causes. The figure effectively illustrates the most important drivers of demand by grouping the categories or elements in descending order of their influence on drug demand [7].

The Pareto chart is a useful tool for pinpointing the "vital few" classes or elements that significantly influence drug demand. It enables scholars and decision-makers to concentrate their attention and resources on these significant areas first. Stakeholders can create focused interventions, improve inventory management methods, and more wisely deploy resources by knowing which categories or factors most influence demand.

The Pareto graphic also makes it easier to have data-driven debates and make decisions. Through the visual portrayal of complex information, stakeholders may better understand the distribution of drug demand and pinpoint areas for improvement. The Pareto chart can be used in the study to gain a more thorough understanding of the main factors influencing the demand for drugs, which will help direct future resource allocation and decision-making processes.

Utilising the aforementioned approach provided valuable insights and enabled a deeper understanding of the subject matter;

Below are the insights we have drawn from the Pareto Chart of Medicines in terms of Total Cost, Total Quantity, and Profit

- The top 10 medicines constitute 49.61% of the total cost. The top 60 medicines constitute 80% of the total cost.
- The top 10 medicines constitute 35.46% of the total Quantity. The top 64 medicines constitute 80% of the total Quantity.
- The top 10 medicines constitute 55.47% of the profit. The top 35 medicines constitute 80 % of the profit.

E. Model Approach

Our drug forecasting model serves as an example of realistic and evidence-based predictive model’s ability to revolutionise the management of vital medicine stock levels and store replenishment. We can maximise access to essential medications while lowering safety inventory and cutting waste by utilising precise and data-driven predictions. Our forecasting model, which is specially designed for predicting drug demand, takes into consideration both the complexity of the pharmaceutical supply chain and the peculiar properties of healthcare products. We strive to reduce forecasting errors and improve the precision of our predictions through ongoing improvement and refinement. We can produce forecasts that are closer to the demand point by combining our model with supply chain activities and using real-time data, leading to more accurate and trustworthy insights.

The main goal of the research was to increase the predictability of drug demand. We built several different forecasting models, including Recurrent Neural Network (RNN), Bidirectional RNN (BI RNN), Long Short-Term Memory (LSTM), Bidirectional LSTM (BiLSTM), Gated Recurrent Unit (GRU), and Bidirectional GRU (BiGRU), [Fig.2, 3] to do this. Each of these models was created independently as a part of our research strategy.

- Recurrent Neural Network (RNN) [Fig.2, 3]: RNN is essential in anticipating medication demand because of its capacity to handle sequential data and capture dependencies between previous and present inputs. RNN can find hidden patterns and trends in past sales data that might not be visible using conventional statistical techniques. The RNN's memory cells allow the model to keep track of data from earlier time steps, enabling it to factor previous observations into its forecasts. Since historical sales data significantly affects future demand, this skill is particularly useful in predicting drug demand. RNN helps in the correct prediction of drug demand, assisting in the best management of medical inventory, by using its grasp of temporal dependencies [5].

- Bidirectional RNN (BI RNN) [Fig.2, 3]: By processing sequential data in both forward and backward orientations, BI RNN improves prediction skills. The model may acquire a more complete understanding of the sequential patterns and dependencies contained in the drug demand data thanks to this bidirectional processing. BI RNN can find subtle trends and patterns by taking information from both past and future inputs, which may not be visible with unidirectional techniques. The forecasting algorithm can now predict drug demand more precisely thanks to this bidirectional analysis, which also helps to manage medical inventory effectively.
- Long Short-Term Memory (LSTM) [Fig.2, 3]: Hospitals can use Long Term Short Memory (LSTM) to anticipate when patients will require medications. This approach was selected since it is well recognized to be highly accurate at foretelling stationary data.
- By overcoming the vanishing gradient issue and identifying long-term dependencies in sequential data, LSTM improves predictive skills. Similar to the RNN, LSTM plays a critical role in medication demand forecasting by successfully simulating complicated patterns and trends over time. This helps to estimate future demand accurately. The LSTM can record both short-term fluctuations and long-term dependence because it has memory cells and gating mechanisms that allow it to selectively store and use information from prior inputs. Similar to the RNN, this ability of the LSTM aids in improving forecasting accuracy and optimising the medical inventory management system [4].
- Bidirectional LSTM (BiLSTM) [Fig.2, 3]: A vital part of the forecasting model, Bidirectional Long Short-Term Memory (BiLSTM) expands on the strengths of LSTM and takes on similar problems. By successfully capturing long-term dependencies and intricate patterns in sequential data, BiLSTM, which is similar to LSTM and RNN, is essential in accurately forecasting future medication demand. BiLSTM combines information from past and future inputs by processing the sequential data in both forward and backward directions, giving a more thorough knowledge of the underlying patterns. Similar to LSTM and RNN, the use of BiLSTM improves forecasting accuracy while optimising medical inventory management procedures.
- Gated Recurrent Unit (GRU) [Fig.2, 3]: For precisely forecasting drug demand and improving medical inventory management, the forecasting model uses the Gated Recurrent Unit (GRU), in conjunction with other cutting-edge machine learning approaches. The GRU is a type of recurrent neural network that is made to handle sequential data and identify temporal relationships. GRU effectively captures both short-term oscillations and long-term patterns in drug demand by employing gating mechanisms, which let it retain and update knowledge from past inputs in a selective manner. By adding GRU to the forecasting model, its predictive powers are improved, enabling precise projections and assisting in the effective management of medical inventory [6].
- Bidirectional GRU (BiGRU) [Fig.2, 3]: The forecasting model must include the Bidirectional Gated Recurrent Unit (BiGRU), which collaborates with other cutting-edge machine learning methods like RNN, BI RNN, LSTM, BiLSTM, and GRU. To correctly forecast drug demand and improve medical inventory management, BiGRU is essential. The BiGRU is made to handle sequential input and capture temporal dependencies, much like other recurrent neural networks. BiGRU obtains a thorough grasp of the underlying patterns and trends by analysing data in both forward and backward orientations.
- Ensemble Model (Gradient Boost) [Fig.2, 3]: A predictive modelling technique called an ensemble model combines the results of various independent models to create a single, more reliable prediction. An ensemble model was used to increase prediction accuracy when projecting drug demand for the best management of medical inventories.
- The forecasts from different individual forecasting models, including RNN, BI RNN, LSTM, BiLSTM, GRU, and BiGRU, were integrated with the ensemble model. Each of these models has particular advantages and traits. The ensemble model sought to improve prediction performance by utilizing the variety of these models and their capacity to capture various facets of drug demand trends.

F. Research Findings

In our research, we conducted model building and evaluation using different resampling frequencies, including daily, weekly, and monthly, to assess their impact on forecasting accuracy.

The performance of each model was evaluated, and the results are presented below.

Table 1 MAPE Values of Each Model

MAPE	**Meropenem**		**Noradrenaline**		**Pantoprazole**		**Paracetamol**	
	Train	**Test**	**Train**	**Test**	**Train**	**Test**	**Train**	**Test**
RNN	41.7	21.8	50.5	56.3	9.52	10.7	53.6	75.8
BI-RNN	43	69	43	118.8	21.6	7.9	33.3	6.4
LSTM	44.7	81.8	30.7	48.4	21	9.69	30.3	6.7
BI-LSTM	35.7	76.8	32.2	76.1	22.8	14.6	22.1	13.9
GRU	64.7	78.8	50.5	56.3	65.7	82.7	53.6	75.8
BI-GRU	36.7	67.8	32	67.2	20.7	10.9	22.3	11.7
Gradient Boost	5.1	1.98	2.82	4.91	0.78	2.78	1.34	2.5

We evaluated the performance of various models for forecasting drug demand, namely RNN, BI-RNN, LSTM, BI-LSTM, GRU, BI-GRU, and the Ensemble model (Gradient Boost). We measured the Mean Absolute Percentage Error (MAPE) for each model using different drugs, including Meropenem, Noradrenaline, Pantoprazole, and Paracetamol. The MAPE values were calculated [Table.1] for both the training and testing datasets.

For the drug Meropenem, the Gradient Boost model demonstrated the lowest MAPE values. While other models such as RNN, BI-RNN, LSTM, BI-LSTM, GRU, and BI-GRU showed higher MAPE values ranging from 21.8% to 81.8% [Table.1], the Gradient Boost model achieved significantly lower MAPE values of 1.98% for training and 5.1% for testing [Table.1]. This suggests that the Gradient Boost model provided more accurate predictions, benefiting from its ensemble nature and ability to capture complex patterns in the data.

Therefore, the Gradient Boost model was selected as the preferred model for drug demand forecasting for Meropenem.

G. Evaluation of the Forecasting Models

To evaluate the performance of the ensemble forecasting model, we employed various metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). These metrics allowed us to assess the accuracy and robustness of our predictions.

Mean Absolute Percentage Error (MAPE) is a commonly used metric in forecasting to measure the accuracy of predictions relative to the actual values. It calculates the percentage difference between the predicted values and the corresponding actual values, averaging these differences across the entire dataset.

MAPE is calculated using the following formula:

MAPE = (1/n) * Σ(|(Actual_i - Predicted_i)/Actual_i| * 100)

Where:

- Actual_i represents the actual value of the target variable for the i-th observation.
- Predicted_i represents the predicted value of the target variable for the i-th observation.
- n represents the total number of observations.

MAPE provides a relative measure of forecasting accuracy, allowing us to understand the average percentage difference between our predictions and the actual values. A lower MAPE indicates higher prediction accuracy, while a higher MAPE suggests a larger discrepancy between predicted and actual values [4].

By calculating the MAPE for our ensemble forecasting model, we assessed its performance in accurately predicting drug demand. Additionally, we compared the MAPE scores of the individual models (RNN, BI RNN, LSTM, BiLSTM, GRU, BiGRU) with that of the ensemble model to determine the improvement achieved through the ensemble approach.

In addition to MAPE, we also considered other metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) to comprehensively evaluate the performance of our ensemble model. These metrics provided additional insights into the absolute differences and dispersion of our predictions compared to the actual values.

Through rigorous evaluation and comparison, we aimed to validate the effectiveness of our ensemble forecasting model and demonstrate its superiority in predicting drug demand**.**

- ➢ *Reorder Point*

Reorder point is the minimum inventory level at which a new order should be placed to prevent stockouts. It is required to ensure a continuous supply of products, handle demand fluctuations, and optimise inventory efficiently

- ➢ *Reorder Point Calculation:*

Reorder point Formula: (Average Daily Use x Average Lead Time in Days) + Safety Stock

To find Reorder point multiply the average daily usage by the average lead time in days, and then add the safety stock to determine the reorder point

- ➢ *Method For Determining The Safety Stock*

Safety stock refers to the additional stock held by a company or organisation as a buffer to mitigate the risk of stockouts or supply disruptions. It serves as a cushion to account for uncertainties in demand, lead time, and supply variability. The purpose of safety stock is to ensure that there is sufficient inventory on hand to meet customer demands during unexpected fluctuations or delays in the supply chain

To calculate the Reorder point, we must first be aware of our safety stock. Safety stock is calculated as follows:

Safety stock = (maximum daily usage x maximum lead time in days) – (average daily usage x average lead time in days)

To calculate the safety stock, businesses take into account the maximum daily usage, which represents the highest quantity of a product used or sold in a single day, and the maximum lead time in days, which is the longest duration it takes for an order to be placed with a supplier and for the inventory to be received. Subtracting the product of the average daily usage and the average lead time in days from this value results in the safety stock.

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Safety stock serves as an additional buffer to mitigate the risk of stockouts or supply disruptions caused by fluctuations in customer demand, lead time variability, or other unforeseen circumstances. By having safety stock in place, companies can ensure that they have enough inventory on hand to meet customer demands even during unexpected situations, helping maintain a smooth and reliable supply chain operation

Where:

- *Average Daily Drug Consumption:*
  The average quantity of drugs consumed per day based on historical data.

- *Average Lead Time in Days:*
  The average time it takes for the drugs to be replenished once an order is placed with the supplier.

- *Safety Stock:*
  The buffer quantity of drugs kept on hand to account for unexpected fluctuations in demand or delays in the replenishment process.

By substituting the appropriate values into the formula, we can calculate the reorder point for our drug forecasting model. This value represents the inventory level at which a new order should be placed with the supplier to ensure a continuous supply of drugs and prevent stockouts.

III. RESULTS AND DISCUSSION

The study aimed to enhance drug demand prediction through data-driven strategies and advanced machine learning models. The models employed, including RNN, BI RNN, LSTM, BiLSTM, GRU, BiGRU, and the Ensemble model (Gradient Boost), were assessed for their accuracy in forecasting medication demand based on historical sales data. Notably, the Gradient Boost model outperformed others, achieving MAPE values as low as 1.98% for training and 5.1% for testing, compared to other models with values ranging from 21.8% to 81.8%. This underscores the effectiveness of the Ensemble approach, demonstrating its ability to capture complex patterns and dependencies within the data.

The success in achieving such low MAPE scores for specific drugs demonstrates the effectiveness of our data-driven approach and the power of advanced machine-learning techniques in forecasting drug demand. By accurately predicting the demand for each drug, healthcare organisations can optimise their inventory levels, reduce wastage, and ensure the availability of critical medications for patients.

The health ministry can identify regional health trends by using the forecasting drugs inventory management model outlined in this study. The model may identify illness outbreaks, highlight healthcare inequities, personalise interventions, effectively allocate resources, assess program performance, and encourage collaborative decision-making by looking at drug demand patterns at the regional level. With the use of these insights, the health ministry is better equipped to plan, use resources more effectively, and enhance regional health outcomes.

IV. CONCLUSION

With a MAPE score of below 5%, our model for forecasting drug demand and optimising medical inventory management demonstrates exceptional reliability. This level of precision establishes a strong basis for its application in numerous other healthcare initiatives, ensuring its effectiveness in addressing a wide range of challenges and opportunities within the field.

The proposed implementation of this model involves integrating real-time data streams from healthcare sources such as hospitals and public health agencies. The proactive management of inventory and timely availability of important pharmaceuticals made possible by this innovative technique helps healthcare professionals improve patient care while also maximising the management of medical inventory.

DECLARATIONS

- *Acknowledgments:*

- We acknowledge that with the consent from 360DigiTMG, we have used the CRISP-ML(Q) methodology (ak.1) and the ML Workflow which are available as open-source in the official website of 360DigiTMG (ak.2).

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- The authors declare that no funds, grants, or other support were received during the research or the preparation of this manuscript.
- The authors declare that they have no relevant financial or non-financial interests to disclose.

- *Data Availability Statement:*
  The datasets used, generated and/or analysed during this study are not publicly available due to internal Data Privacy Policy but are available from the corresponding author on reasonable request.

COMPLIANCE WITH ETHICAL STANDARDS

- *Disclosure of Potential Conflicts of Interest:*
  The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

- *Research involving Human Participants and/or Animals:*
  It is declared by all the authors that there was no involvement of any human and/or animal trial or test in this research.

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- *Informed Consent:*

As there were no human subject involved in this research hence a informed consent is not applicable to the best of the authors' understanding.

- *Conflict of Interest Statement:*

The authors declare that there are no conflicts of interest that could influence the results or interpretation of this manuscript. This research was conducted in an impartial and unbiased manner, and there are no financial, personal, or professional relationships that might be perceived as having influenced the content or conclusions presented in this work.

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