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A Machine Learning Approach to Predict Drug Stock Based on Consumption Patterns for Dispensary Management System

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ABSTRACT

Today's global business trends are causing a significant and complex data revolution in the healthcare industry, culminating in the use of artificial intelligence and predictive modeling to improve health outcomes and performance. This study uses data on drug expenditure transactions based on prescriptions given by doctors to patients indispensaries based on time series to be able to predictdrug needs in the coming period. The calculation of the drug needs to be done optimally. Because the excess drug will be a management problem in the drug and pharmaceutical warehouses and expire, thelack of medicine will harm patient health and reducepatient satisfaction and trust. Being part of the ERP,the time series-based demand forecasting predicts drug needs based on the use of drugs in prescribing patients in Dispensary. The calculation of the prediction of drug needs for the coming period is based on the availability of data on drug expenditurein the previous period. The dataset, which was referred to is based on consumption data from 2018 to 2021. The results of research on the predicted value of the model and the actual value show the feasibility and effectiveness of using the RFR network to predict the optimum drug needs in the coming weeks. The dataset is of a Dispensary management system. The dataset comprises Historical sales, Drug Information, and drugs whichneed forecasting. Our study concentrated on the application of machine learning (ML) to forecast future trends in the demand for essential drugs in the dispensary management systems. Demand forecasting is required at a quarterly level. Carry- Over products are those products that have historicaldata present and New products do not have anyhistorical data present. The following models were created and applied: linear regression, artificial neural network, and random forest According to our findings, the random forest model performed well as a forecasting model for the demand for essential medicines. Finally, data-driven predictive modeling with machine learning (ML) could become the cornerstone of health supply chain planning and operational management.

Keywords: Artificial Intelligence, Dataset, Spark, Hadoop applications, Prediction model, Optimization Model, Drug stock Formulary.

1. INTRODUCTION

Drug management in a dispensary is one of the most important components. Drug management aims to ensure that the required drugs can always be available at any time needed in sufficient quantities,the right type, on time, guaranteed quality and used rationally. Inefficient drug management has a major impact on the Dispensary's financial system. One of the effective drug management processes is to ensure the availability of drugs in terms of both the right type and amount under need to avoid the lack and excess of the drug. To maintain the availability of drugs, the team at the dispensary that involves various professions must agree and select drugs thatwill be used and circulated. The results of this team'sagreement are often referred to as the dispensary Drug Register or dispensary Drug Formulary. If the Hospital Formulary already exists, then writing prescriptions and available drugs must follow the rules as stated in it. Hospital pharmaceutical installations overcome this condition by planning drug procurement as data to be used as a Drug Formulary. The formulary evaluation must be done periodically; updating the formulary is an important factor in optimizing the use of formularies [1]. The compilation process of drug use precedes planning, which is a recapitulation of drug use data in the health service unit, which is used as a basis for calculating optimum stock [2]. Compiling a formulary for selected drugs requires a large amount of historical drug administration data for patients thatcan be seen by a certain period. Finding out this information can be done through the utilization of patient prescription data in the dispensary. These data are a very large and growing set of datasets, known as big data. Big data can be used to determinethe formulary of drugs in hospitals [3] by conductingdata mining of these data to know the future needs ofdrugs.

During this time the dispensary plans for future drug needs through two analyzes, namely ABC analysis and VEN analysis. Both analyzes offer a value of stock requirements that are not based on history or a good trend of drug expenditure because they only consider the condition of drug stocks one year before and without considering the optimizationaspects. This improper planning results in wasteful budgeting, stagnant, and stock out. This study proposes a data mining approach to planning drugs that need to be included in hospital formularies using deep learning. The most suitable algorithm for time series data form in the form of drug expenditure in the dispensary is Long Short Term Memory (LSTM) [4][5] which is the development of the Recurrent Neural Network (RNN) algorithm.

1. LITERATURE REVIEW:

Predicting future trends provides additional value for improved healthcare system management in today's global business trends and step forward technologies [1]. After all, the healthcare system is going to undergo a huge data revolution, with Artificial Intelligence (AI), predictive analytics, and business intelligence ready to increase efficiency andenhance health outcomes [2]. AI, especially ML, expected on widely employed to predict previously unknown patterns in disease, treatment, and care by 2030, according to the World Economic Forum [3]. Business growth in any sector as it is for healthcare is all about adapting and pivoting to stay relevant in the market. You cannot expect to be in business if your consumer needs change, but your supply chain does not. Even though the health supply chain is, rapidly evolving, predictive models can help maintain a high level of performance by providing insights into patterns based on historical data. Medicines quantification is the process of calculating the quantities and prices of Commodities necessary for a certain health program (or facility) and determining when the medical item should be delivered to guarantee that the intended program or service is continually given to the intended users [4]. For reliable and successful quantification of essential medicines, information about consumption data, procurement period, prescriptions, minimum and maximum inventory levels, inventory rotation, morbidity data, along with compliance with the use of an essential medicines list (EML) is required [5,6]. This highly complex process entails predicting the number of essential medicines required and serves as a basis for determining the appropriate quantity to procure.

There are substantial barriers to developing andenhancing the efficiency of a well-organized supply chain of critical medications due to their high complexity, which is increasingly adding to people's delayed access to essential medicines [7]. Furthermore, there is no room for inaccuracy when itcomes to an important and functioning health supply chain that assures the availability of essential medicines since it might harm people's health, socio-economic position, and day-to-day activities. Supply uncertainty for essential pharmaceuticals and life- saving products can be reduced with accurate demand forecasts [8,9]. In light of available resources, supply chain information, and inventory levels, the required quantities of essential medicinesshould always be determined using an appropriate approach, such as prediction models, economic orderquantity, or the Min/Max formula [10]. It is fair-minded to assume that collaborative forecasts based on end-user consumption data will help upstream supply chain managers minimize prediction errorwhen employing forecasting models in the management of essential medicine supply and inventory control [11]. Whereas has guaranteed that its citizens have access to quality healthcare and affordable medicines, the goal of this study is to see whether ML techniques might be used to improve demand forecasting accuracy and therefore optimizethe availability of essential medicines [12]. Linear regression, artificial neural networks (ANN), andRandom Forest have all been studied, suggested, andused in supply chain fields, with amazing outcomes on a range of difficulties [13,14]. Therefore, it is potentially relevant to undertake the benefit of ML application in the health supply chain for predicting the future consumption of essential medicines. This study aims to apply an ML approach to predict future trends for essential medicines consumption in HPCL by using historical data extracted from the Dispensary management information system (DMS),which is an application used in the management of health commodities.

2. METHODOLOGY:

Data has been used and processed to be appropriate in the prediction process. In this regard, one of the most essential goals of time series analysisis the prediction of future data, which may be utilizedin the health supply chain [11]. While making strategic decisions under uncertainty, predictive analytics and models offer a great prospect. A

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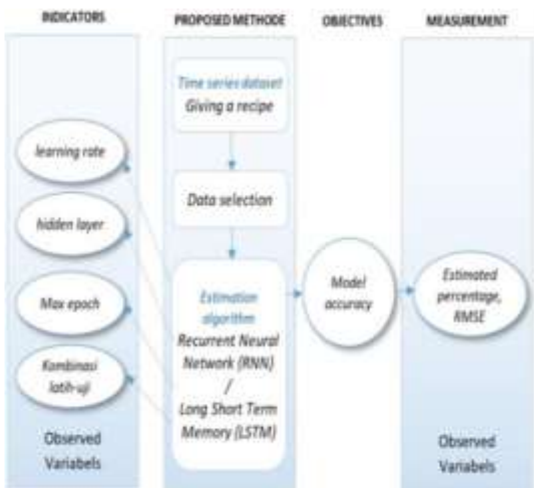
univariate time series, in practice, is a collection of observations of a single random variable across the period. The more the uncertainty in expectations, the higher the degree of inaccuracy in time series forecasting [16,17]. Subsequently, from different viewing platforms that can be applied in the forecast process, a suitable technique should be selected in consideration of the nature and amount of available historical data.

The proposed method for obtaining knowledge so that it can be used to estimate drug needs in the coming period is to use a deep learning approach in the form of Recurrent Neural Network(RNN) / Long Short Term Memory (LSTM)algorithm, by previously selecting data that suitable for testing. The framework for this research is shownin Figure 1.



3. DATA UNDERSTANDING

The data used in this study is sourced from the Dispensary Management System (DMS), one of the data modules is the administration of drugs to patients carried out by the Pharmacy department. Prescriptions are received from doctors who treat patients, both emergency patients, Outpatient and Inpatient Poly. Drug administration data that is already contained in this database is a drug that is available and given to patients.

S.NO	ITEM	DRUG NAME	BATCH NO	MANUFACTURE DATE	EXPIREDDATE	STOCK
1	1039	ACCELO - P	ZOBOO21	31/12/2017	31/12/2019	120
2	1024	DOLO 650 MG	GS6L22	6/05/2019	6/12/2021	600
3	1124	COFSILS	FH5678	4/12/2019	31/05/2021	550
4	1654	PANTOP 40 MG	CG4D78	9/4/2018	10/12/2020	750
5	1548	paracetamol - sachet	MG31J7	12/04/2018	5/10/2020	1000
6	1342	AZITHROMYCIN 500 MG	LK6S45	12/05/2018	3/3/2020	250

Data were obtained from three interrelated tables namely data from the drug STOCK table, ISSUE MEDICINE tables, and RECEIPT tables. After compiling, a table with attributes as in table 2 is obtained.

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S. NO	MEDICINE	RATE	ISSUED QTY	TOTAL QTY	ISSUE DATE
1	ACECLO -P	30	20	100	02/10/2019
2	DOLO 650MG	40	60	540	05/03/2020
3	COFSILS	20	100	450	10/04/2021
4	PANTOP40 MG	100	120	630	06/08/2018
5	paracetamol -sachet	10	200	800	20/08/2020
6	AZITHRO MYCIN 500 MG	50	30	220	07/06/2018

Data drawn from Dispensary Management System is prepared in steps as shown in Figure 2. Data was collected from 2018 to December 2021 with a total transaction data of 5,547 records. From searching the list of drug names, there are 105 drug data records.

This study did not use all drugs but selected 6 types of drugs with criteria appearing regularly every week. With this criterion, the drug chosen is not the drug with the largest amount of expenditure. There e a certain number of weeks of the period found themost drug expenditure, but the drug does not appearroutinely weekly so the drug was not selected in the study. After sorting, obtained 6 drugs used in this study. All transaction records are carried out in the recapitulation process of spending to get a weekly time series for each drug so that the order of time series data is 156 weeks starting from January 1, 2016. Recapitulation is not done in units of days, consideration to predicting the number of drug needsin the future coming will not be planned for the day.The count in days is too narrow and even takes time and energy to make the planner. Planning for medication needs at a dispensary is usually carried out for a specific week or month to come.

To formulate the amount of drug expenditure from each day into a week, carried out through the MySql database. Then the data is pulled directly from the MySQL database source and exported into the * .csv file format. The trend of drug expenditureevery week. It can be seen that the trend is very non-linear and it is very difficult to capture trends using this information.

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4. MACHINE LEARNING APPLICATION FORPREDICTIVE MODELLING:

Whitelist using ML, we trained the model on one set of observations and test it on another differentset of observations to learn the model's generalizability of new data. We have split data intotwo sets. The train set is data from January 2018 untilDecember 2021, and the test set was from July 2018until June 2021. We used test data from January to December 2021, but the test data was also required to have 12 months as training data to have the same dimensions. For the sake of retaining the enormous training dataset, we included the prior 6 months to balance dimensions without removing them fromtraining. The data were grouped by year and month for better prediction as we want to predict the quantity of the specific drug on basis of a month as indicated in Table 3.

Set	Variable	Count	Mean	StandardDev	Median	Min	Max
Train	Amount	149,740	834.15	1076.45	292	14	4335
	Total amount	14,321	18,871.056	24,143.68	6515	14	153,839
Test	Amount	39,966	868.95	1110.27	281	14	4335
	Total amount	3502.00	9841.05	10,307.60	5564.00	14.0	53,952.00

Table 3 presents the summary statistics of the number of drugs consumed on both train and test sets before andafter grouping them by year, type of drugs, and districts to have data

On the train set, we had 149,740 observations,with a mean of 834.15 quantity of drugs consumed, a standard deviation of 1076.45, a median of 292, a minimum value was 14, and a maximum value was 4335. For grouped data, the number of observations was 14,321, mean of 18,871.056, a standard deviation of 24,143.68, a median of 6515, a minimum value equal to 14, and a maximum value equal to 153,839. With the test set, we had 39,966 observations, with a mean of 868.95 quantity ofdrugs consumed, a standard deviation of 1110.27, a median of 281, a minimum value was 14, and a maximum value was 4335. For grouped data, the number of observations was 3502.00, a mean of9841.05, the standard deviation of 10,307.60, a median of 5564.00, the minimum value equal to 14, and a maximum value equal to 53,952.00

5. PREDICTION OF ESSENTIAL MEDICINE DEMAND WITH MACHINE LEARNING TECHNIQUES

Predictive modeling is an approach that uses a mathematical method to foresee future occurrences or outcomes, as well as to predict future trends, by searching for patterns that have occurred in the past or by analyzing historical data [20]. In this point of regard, businesses with limited resources, based on experience, can use readily available software to develop reliable and accurate estimates in a timely and cost-effective manner using excel spreadsheets or other relatively simple excel- based software [19]. Even though these are simple procedures with limited insight, it was evidenced that they are indeed widely used with an estimated rate of 82.1% [20].Indeed, in the field of health supply chain, the purpose of predictive modeling is to answer theconcern regarding the use of known past behavior,for anticipating the most likely scenario to happen inthe future [21]. In this study, the linear regression, ANN, and Random Forest models were used topredict future trends for essential medicines. Linear Regression: Linear regression is a mathematical function and supervised ML model that predicts newdata using input data with labels. The model looksfor the best fitting linear line between the responseand the explanatory components. It's used to makepredictions, particularly when the answer variable isnumerical or quantitative [22].

The following is the linear regression equation

$Y = b0 + b1X1 + b2X2 + b3X3 + \ldots\ldots\ldots\ldots + bnXn$ (1)

B 0 is the intercept, *b*s are the coefficient, and X arepredictor variable.

Random Forest: Random Forest is an ensemble learning technique for regression and other tasks thatbuilds a huge

number of judgmental choices during training. As the name indicates, a Random is a tree- based ensemble in which each tree is determined bya sequence of random variables [23]. In more formalterms, we assume an unknown joint distribution PXY for a p-dimensional random vector X = (X1. . .
Xp) T expressing the real-valued input or forecaster variables and a random variable Y indicating the real-valued response (X, Y). The aim is to explore aprediction task f(X) for predicting Y. The random forest algorithm which has been used is composed of 18,000 estimators (n_estimators), 50 max depth (max_depth), 14 maximum features (max, features), and 4 minimum sample leaf (min_sample_leaf), and a random state (random_state) set to zero [23,24].

Artificial neural network: ANN is a modeling technique based on the human nervous system that allows for learning by example from representative data to explain a real-life event or a process leading to decision—making. As indicated in Figure 3, a defining aspect of ANN is its capacity to build empirical connections between independent and dependent variables, as well as extract nuanced information and sophisticated knowledge from representative data sets. ANN models provide numerous advantages over regression-based models, such as the capacity to manage outliers, because the links between variables may be formed without making any assumptions about a detailed descriptionof the events [22].

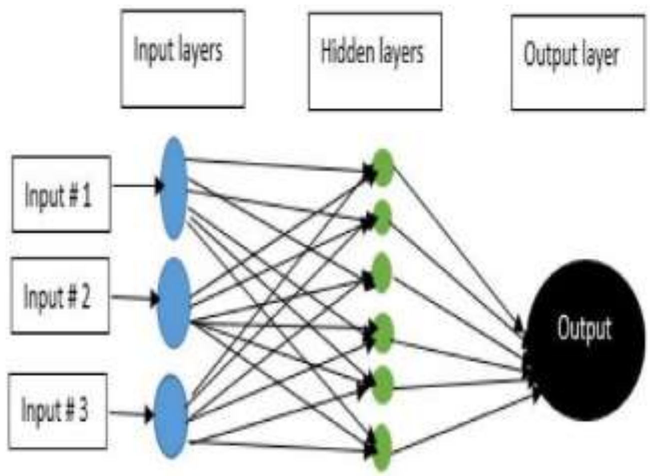

Fig: The basic structure of an artificial neuralnetwork

The basic structure of ANN used wascomposed of 11 dense layers. The last one as output,the first dense layers were composed of 300 units, with an input shape of 53 equal to the number of predictors, the second dense layer was composed of 300 units, the third and fourth dense layers were composed of 150 units, the fifth and sixth dense layers had 75 units, the seventh and eighth had 50 units, ninth and tenth had 25 units, the last dense layer which is output layer had only one unit for prediction. The activation function used is relu, l2 regularizer, and was used with a rate of 0.08 toregularize the weight to avoid over-fitting. In our study, we used the Adam optimizer to build themodel, with mean squared error as the loss function,mean squared error and accuracy as training metrics, 64 batch size, and 1000 epochs. Forecast Bias, Mean Absolute Deviation (MAD), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE) are the most widely functional demandforecast accuracy metrics to assess the validity of models, according to prior research [8,25]. The accuracy metrics applied, and how it is introduced, deployed, and tracked are all influenced by the type of output generated. Realistic and evidence-based predictive modeling has the potential to provide optimal critical medicines availability while decreasing safety inventories, reducing waste, and continual improvement in the management of essential medicines stock levels and store replenishment [26]. Despite the existence of links between accuracy-based metrics and levels of aggregated prediction across commodities and forecasting periods, as well as the matching of statedaccurateness and standards, forecasting errors remain. Of course, forecasting errors are known to vary depending on to which extent forecasters are involved in the supply chain activities. However, forecasts made closer to the demand point will be more accurate. However, forecasts made further the management of the supply chain by heightening the control of incidental forecast inaccuracies [27].

6. MODEL EVALUATION:

After training, we evaluated the model by comparing its predictions to the true target on training data. However, we also evaluated our model on new data that has not been utilized in training. R-square (R2) and root

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mean square error (RMSE) wasused to evaluate the model.

Root mean square error: Considering that in RMSE, the errors are squared before being averaged.This means that the RMSE weights larger errors more heavily. This implies that when large mistakes are present and have a substantial influence on the model's performance, RMSE is significantly more effective. This feature is beneficial in many mathematical computations since it avoidscalculating the absolute value of the mistake. In thismetric as well, the lower the value, the better the model's performance [25].

R-square (R2): This metric indicates how well a model matches a given dataset. It is also referred to as the coefficient of determination. The R2 indicates how close a regression line (the displayed predicted values) is to the actual data values. In the run- through, the R2 value varies from 0 to 1, with 0 indicating that the model does not fit the data and 1 indicating that the model perfectly fits the dataset [25].

7. DISCUSSION OF EXPERIMENTALFINDINGS

As presented in Table 4, from our experimental results, the Random Forest model is better than other applied models, as it has low RMSEand the model fit 88 percent of the training dataset and 76 percent of test data than Linear regression which fit 80 percent on the training dataset and 74 percent on the test set, as well as 87 percent for the neural network on the training set and 55 percent onthe test set.

Model	Set	RMSE	R-Square
Linear Regression	Train	0.82	0.80
	Test	0.89	0.74
Random Forest	Train	0.64	0.88
	Test	0.84	0.74
Neural Network	Train	3429.98	0.87
	Test	6922.77	0.55

Table 4. Presentation of Model Results.

The Linear Regression model predicted approximately equal to the actual values, and it was able to predict the trend. The Random Forest model predicted approximately equal to the actual values; it was able to predict the trend very well. The Artificial neural network model predicted approximately equal to the actual values, it was able to predict the trend but, in the end, the predictions arehigher different than the actual. Root mean squared error of Linear regression on train data equal to 0.82,on test data equal to 0.89, for Random Forest is 0.64on a train set, on a test set is 0.84, and for the neuralnetwork is 3429.98 on a train set, on a test set is 6922.77. Neural network model actual numbers wereused to predict as the log-transformed values were not able to converge so we kept the real values in model training. R-square of Linear Regression on train data equal to 0.80, on test data equal to 0.74, for Random Forest is 0.88 on a train set, on a test set is 0.76, and for the neural network is 0.87 on a train set,on a test set is 0.55. According to our experimental results, the Random Forest model is better than others as it has low RMSE and the model fit 88 percent of the training dataset and 76 percent of test data than Linear regression which fit 80 percent of the training dataset and 74 percent on the test set, aswell as 87 percent for the neural network on the training set and 55 percent on the test set. The higher difference of train and test metrics, in that case, the model overfitted, all the models have overfitted but neural network overfitted highly. More complex methods for predicting difficulties that use a system dynamics modeling approach have arisen in recent decades, contributing to the creation of models that track the control and management of diseases and theuse of essential medicines over time and form loops in prediction models [28]. According to previous studies, while there is plenteously data that are usefulfor more precise and reliable demand forecasting (e.g., changes in disease control, treatment guidelines, and their effects on consumption of essential medicines), data related to treatment and medicines prescription is limited due to a variety of factors including different data formats, a lack of management tools for data integration, data collection times and real fact from data, as well as lack of new and advanced models for vastly increased prediction insights [29]. Modeling, for example, is indeed a useful way to verify prediction models since it uses data from the past. Data visualization also aids collaborative decision-makingand forecasting future demand for vital drugs in the healthcare supply chain. In the management of healthsupply chains and pharmaceutical commodities, timeseries models are used the most (52 percent) and causal models are used the least (24 percent), according to a 2002 study by Jain, while judgmentalmodels account for 19 percent and mixed or combination models account for 5% [30].

Furthermore, leveraging AI technology

such as ML applications to improve the accuracy in forecasting and demand predictions for essential medicines might potentially improve theiravailability and reshape their well-ordereddistribution [31,32].

The figures of prediction models for essential medicines consumed by month versus the actualnumber of drugs by each model are presented as indicated below

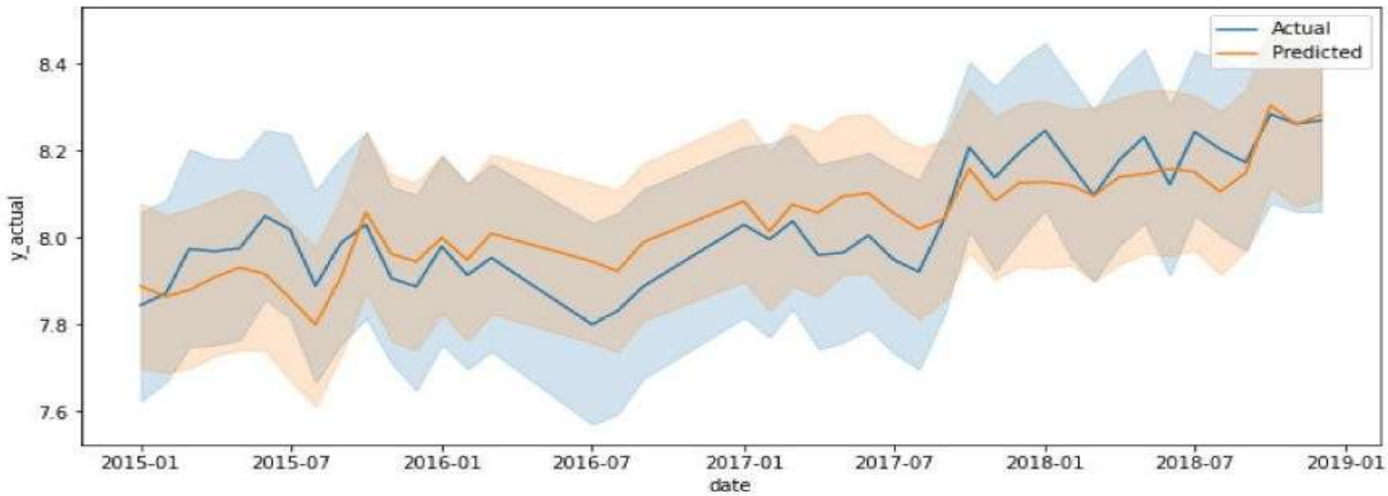

Figure 4. Linear Regression.

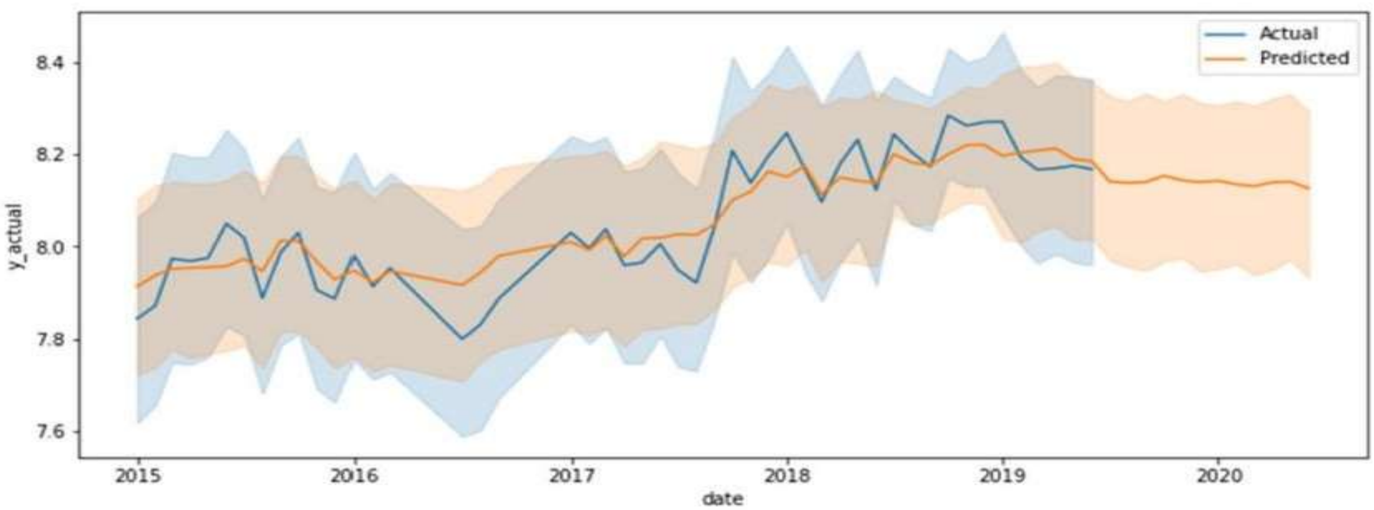

Figure 5. Random Forest.

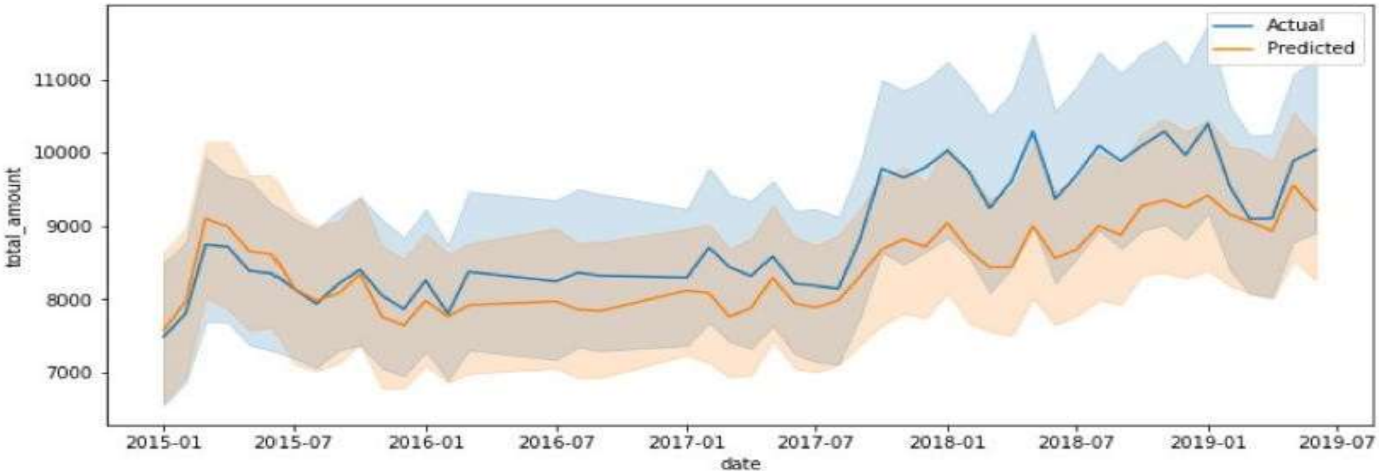

Figure 6. Artificial Neural Network.

8. CONCLUSIONS AND RECOMMENDATIONS

Given that the supply and management ofessential medicines are challenging, and a necessity,there are several obstacles to overcome to maximizetheir availability and increase access to clients who seek them. Applied predictive modeling on essentialmedicines consumption forms a basis for all plannedactivities in the health supply chain. According to research, forecasting is a comparatively recent understanding for the healthcare field, which may explain the popularity of basic approaches mostly conducted using excel Spreadsheets in the past. Ourstudy has focused on the application of ML for predicting the future trend for essential medicines consumption in the Dispensary Management System. Three types of models have been developed including— Linear regression, Random Forest, and Artificial Neural Network models. Two out of three developed models were able to fit the data 75 percentat the training set, and above 55 percent at the test set. The Random Forest model outperformed others at 88 percent on the train set and 76 percent on the test set. The random forest was able to predict data accurately at 88 percent with the train set and 76 percent with the test set and thus it can be used to make predictions for future consumption based on past consumption by inputting the year, month, districts, and drugs. Finally, the findings of our study's experimental examination of threeforecasting scenarios demonstrate that the random forest predicting model has the greatest match to historical demand data, and reduced error estimates across the look at scenarios and trials. Given our findings, we strongly recommend that the random forest model be used to predict the future trend in demand for essential medicines. The availability of medicines will be ensured and optimized by taking such predictions into account. Furthermore, our study revealed very pertinent information that couldhave an impact on the effective and efficient management of the health system. The managementof a reliable and sustainable supply of essential medicines and other lifesaving products. The randomforest model has developed a unique method for effectively forecasting future trends in vital drugdemand, making it a powerful recommendation in the field of the health supply chain.

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