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Applying Neural Networks to Predict Ventilator Demand: A Study of Pakistan's Healthcare Sector

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Abstract

The distribution companies that deal with ventilators in Pakistan face challenges related to inventory control because of inadequate product shelf life, shortages, excess inventory, and unnecessary stock. This study, which focuses on Pakistani ventilator distribution companies, aims to offer a novel approach to sales estimation, avoid unnecessary stock expenditures, and stop clientele loss brought on by ventilator shortages. The results of this study will help determine key elements and standards that Pakistani distributors of ventilators might employ to boost sales. Most ventilator distribution businesses in Pakistan are independent wholesalers that purchase stock from their stores and distribute it to customers. To maximize ventilator distribution firms' sales for various products, this study examined distribution and sales data from 2019 to 2024 for many locations and dates. To create an accurate sales forecasting model for a ventilator distribution company, this research also aims to apply artificial neural networks (ANN) for effective sales prediction. An Artificial Neural Network (ANN) model was trained using a dataset from ventilator distribution businesses and the proposed model produced an accuracy of 90%, which is good for early prediction.

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1 Introduction

Pakistani ventilation distribution companies deal with some difficulties, including controlling enormous inventories, heightened competition, and strict laws that restrict distribution. They have to supply the right amount of ventilators at the right time and location to satisfy the demands of healthcare practitioners. Both surpluses and shortages of ventilators cause losses for the Pakistani ventilator distribution groups, which can be challenging to control. A significant challenge for Pakistan's ventilator distribution industry is figuring out how many ventilators to stockpile and how much to distribute among different medical facilities [1].

Worldwide, there are numerous approaches to maximizing ventilator sales, and numerous studies have been carried out in various locations following their needs. Based on sales data from the previous three months, distribution businesses in Pakistan forecast their sales. The projections for other seasonal sales are based on data from the seasonal sales of the preceding three years. Different statistical approaches are used in different locations to anticipate sales. [2].

Any distribution process needs optimization to properly distribute resources and reduce waste, especially in vital industries like healthcare. Optimized procedures are crucial for industries like E-Commerce, Banking, Automotive, Hospitality, Professional Services, and Information Technology to achieve maximum efficiency and profitability [3]. But there is no place for delays or over-allocation of equipment in the healthcare industry, particularly when it comes to the distribution of ventilators. The ongoing global health issues, which are frequently made worse by climate change, have caused diseases to spread quickly, necessitating an efficient and quick response [4]. While an excess of ventilators leads to resource waste and financial loss, a lack might have disastrous effects. Thus, to guarantee a sufficient and timely supply to hospitals and other healthcare facilities, optimizing ventilator distribution is essential.

The ventilator distribution companies in Pakistan are facing the challenge of equipment degradation, which poses a significant barrier to the timely distribution of ventilators to healthcare facilities [5]. Karachi city alone handles a vast amount of hospital waste daily, including expired or malfunctioning medical devices such as ventilators, along with their parts or packaging materials. Understanding how medical equipment manufacturers determine the longevity and maintenance of their products is crucial. All ventilators have unique designs involving both hardware and software components to provide life-saving respiratory support. Once a ventilator is manufactured, the quality and durability of these components determine the operational lifespan of the device, which is known as the ventilator's usable life period. If the ventilator is utilized within this period and properly maintained, its maximal efficacy and safety can be ensured for patients.

Healthcare facilities must invest in and pay for precise ventilator distribution predictions to maximize resource allocation and reduce shortages [6]. Any organization that wants to save lives must have a robust ventilator distribution system in place since ventilators have a direct impact on patient care, which is directly tied to public health. Accurate forecasting guarantees hospitals have the right supplies, avoiding both critical shortages and overstocking.

This research explores various prediction methods used globally in ventilator distribution, ranging from statistical solutions to MIS (Management Information Systems) solutions for forecasting demand and optimizing supply chains. The study focuses primarily on the Pakistani healthcare sector, specifically its ventilator manufacturing and distribution practices. The distribution structure in Pakistan is characterized by the involvement of a local distributor who connects manufacturers with healthcare providers. Direct engagement between ventilator manufacturers (whether local or international) and healthcare providers is often challenging due to factors such as regional diversity, language barriers, infrastructure, and political conditions. As a result, manufacturers must rely on distributors to navigate these complexities and ensure that ventilators reach hospitals and other healthcare facilities effectively.

The ventilator distribution procedure is shown in Fig. 1. Through online, phone, or in-person orders, the manufacturer directly supplies ventilators to hospitals or medical facilities. As an alternative, the distributor could be hired by the manufacturer to manage the distribution. The distributor then provides ventilators to different healthcare organizations, such as neighborhood medical equipment dealers, minor clinics, and major hospitals. By doing this, it is made sure that ventilators get to the patients who require them in both big and small healthcare settings.

One of the top ventilator distribution companies is the source of the data used in this study to predict sales; they provide ventilators to patients in all four provinces of Pakistan, each of which has more than 780 towns and cities, more than 45,000 pharmacies,

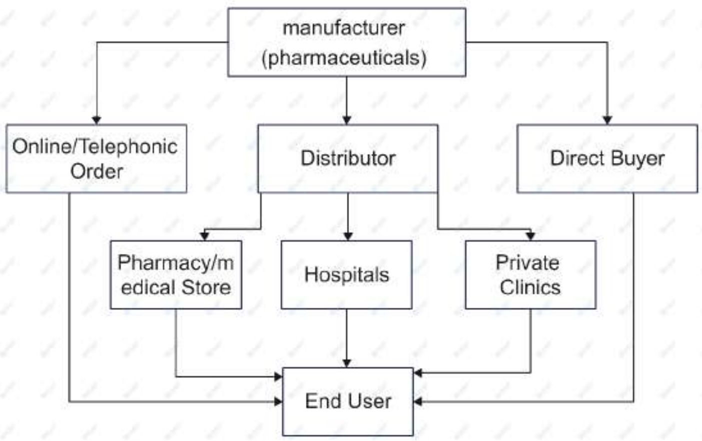

Figure 1. Distribution Cycle of Ventilator

more than 2500 brick and mortar stores, and specialists and institutions [7]. They were available on the same day, every day, twice a day, four times a day, weekly, and every two weeks. They have over 69 depots, sites, and warehouses. The corporation needs a lot of stock in its warehouses to meet client demand. Since the lack of ventilators is intolerable, they typically hold merchandise in their warehouses for 15 to 20 days. [8].

Researchers extensively utilize artificial neural networks (ANN) to address a wide range of issues in various domains of life, especially in areas where traditional modeling techniques prove inadequate. In the context of ventilator distribution, an Artificial Neural Network (ANN) model takes into account several input variables to predict the optimal allocation of ventilators. Compared to statistical models or traditional programming, a trained Artificial Neural Network (ANN) can make predictions and optimize distributions much more quickly [9]. The selection of an appropriate Artificial Neural Network (ANN) architecture is crucial for the accuracy of the model, even when extensive iterative computations are not required to address all distribution challenges. In this study, ventilator distribution is optimized using the ANN Model.

This research aims to develop an accurate sales forecasting model for ventilator distribution companies using artificial neural networks (ANN) to make accurate sales predictions.

2 Literature Review

Many papers on this topic use different techniques, methodologies, or software to optimize sales. For example, some studies used a data-mining approach and regression analysis.

2.1 Theoretical Background

Situated at the heart of the world's healthcare systems, the ventilator distribution industry is highly reliant on forecasting. This procedure is crucial for directing managerial choices in complex modeling intended to forecast future demands, as well as operations, finance, and marketing [10]. Supply chain management is a major concern for ventilation distribution companies. The author of [11] examined these problems and offered solutions, including investing in cutting-edge technologies and developing cooperative ties with suppliers. Similar to this [12] focused on improving the ventilator supply chain's ability to estimate demand accurately by offering insights on the use of machine learning approaches. To address this issue with a more thorough analysis, another author [13] suggested a novel framework for demand forecasting that makes use of cutting-edge machine learning models. This method combines downstream inventory data and supply chain structure data with cross-series training using time series data from various ventilator types.

The efficacy of univariate time series analysis in ventilator distribution forecasting was emphasized by the author in [14], underscoring its strategic importance for healthcare providers. The authors defined data mining approaches in their data classification in [15], a research paper they published on applied data mining techniques for medical data categorization. Business intelligence, which is helpful for ventilator allocation optimization, is aided by data mining. The data mining methods for controlling the distribution of ventilators for different healthcare requirements are clarified in this work. Furthermore, a paper by KPMG titled "Healthcare 2030: From Evolution to Revolution" examines how big data analytics and artificial intelligence are revolutionizing healthcare predictions. The research highlights how these technologies will improve supply chain management for ventilators by greatly increasing the accuracy of demand forecasts and the effectiveness of resource allocation. The report's conclusion highlights how cutting-edge technology has the power to completely transform established procedures and points the way toward a future in healthcare logistics where data-driven decision-making will rule the day.

In [16], the ARIMA methodology and a hybrid Artificial Neural Network (ANN) approach for time series forecasting are used to produce precise sales estimates, which is an important and economical strategy for ventilator distribution companies. In [17], researchers examine how the COVID-19 epidemic has led to an increase in automation in financial technology, emphasizing the significance of accurate stock price forecasting for investment and business plan creation. The study compares two forecasting models, the statistical autoregressive Integrated Moving Average (ARIMA) model, and the deep learning-based LSTM model, using data from the National Association of Securities Dealers Automated Quotations (NASDAQ) stock exchange [18]. The study examines average stock prices from several industries on a daily and monthly basis to guarantee generalizability.ARIMA predictions use past data, but Long Short-Term Memory (LSTM) uses gating mechanisms to record long-term patterns [19]. The findings show that ARIMA performs better than LSTM over the majority of time frames, except for very short-term projections. The research also emphasizes the need for logarithmic data translation for both models and proposes improving LSTM through data incorporation and trend analysis. According to the study's conclusion, a hybrid strategy that incorporates both models could result in a more accurate ventilator distribution projection.

The Pakistan Research Journal of Finance and Accounting published research on the sale forecasting of Merck ventilator Company using the ARIMA Model [20]. The time series data are forecasted by using the ARIMA model which shows that their sales increase from their records. They used the AR and MA models separately. Research study in [21] focuses on leveraging advanced predictive models, ARIMA and LSTM, to improve sales forecasting accuracy. By comparing these models individually and in combination, the study determines the most effective approach for sales prediction. This study concludes that the ARIMA-LSTM hybrid model is superior to individual ARIMA and LSTM models for forecasting sales data. This hybrid approach enhances prediction accuracy, significantly benefiting businesses relying on precise sales forecasts.

The goal of the research described is to create a general model for ventilator distribution prediction called "Business Intelligent Smart Ventilator Distribution Prediction Analysis." The approach that is being given combines Time Series Forecasting (TSF) techniques with real-time application (RTA) tools. Several techniques are used to build Time Series Prediction distribution models, such as artificial neural networks (ANN), fuzzy neural networks, and the ARIMA methodology. They suggested a hybrid technique that combined a newly defined component with an earlier one through real-time data mining. The outcomes show that the suggested strategy is capable of making real-time predictions.

2.2 Problem Statement

The issue of equipment expiration poses a challenge for Pakistani ventilation distribution companies, impeding the smooth distribution of their products to healthcare facilities. Every day, Karachi alone produces a sizable volume of municipal solid trash, which contains abandoned or outdated medical equipment, such as ventilators, as well as the materials used to package or transport it. Patient care and results may be directly impacted by a lack of working ventilators. Thus, it is essential to comprehend how ventilator manufacturers establish the equipment's lifespan and expiration date. Every ventilator is different, and those differences affect how long they last when in use. The ventilator's realistic usability cycle is determined by the quality and longevity of its components after it is constructed. This is the time frame during which the ventilator operates without malfunctioning. A ventilator's performance and dependability are at their best when it arrives at the medical facility within its usable term.

2.3 Objectives

Ventilator disposal and expiration rates are major concerns in Pakistan, where distribution companies need to streamline their processes to properly handle these vital devices. For ventilator distribution, it is essential to apply FEFO (First Expiry, First Out) procedures to guarantee that units approaching their expiration date are utilized first, reducing waste and guaranteeing that the most dependable equipment is available when needed.

Keeping an eye on inventory levels to prevent excessive expenses and shortages that can harm patient care presents another difficulty for ventilator distribution companies. Maintaining a balance between inventory costs and ventilator availability requires effective inventory control.

3 Methodology

This study uses real sales data from a well-known ventilator distribution firm in Pakistan from 2019 to 2024 to determine the main predictors of sales performance. The data comprises many variables, including unit sales, discount rates, advance payments, credit sales, returns, city, area, location, year, month, and day.

The preliminary stages of this study are depicted in Fig 2, starting with data collection and moving through data processing and model construction readying. Data normalization is done in the second step to get it ready for model implementation. Using a variety of graphs and tables, together with statistical tests, graphical representations are produced in the third step. Step four includes sensitivity and regression analysis along with clustering the training data. Applying the processed data to an Artificial Neural Network (ANN) application is the main goal of step five. In step Six, the model is assessed by making sure it is consistent and testing for errors. The model's output is displayed in the last section.

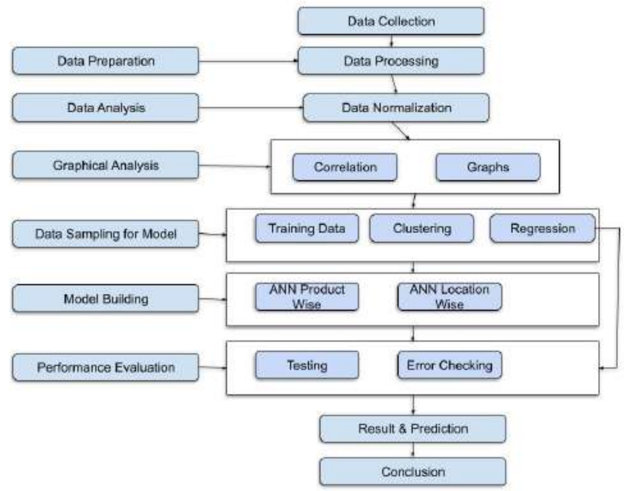

Figure 2. Proposed Model

3.1 Step 1:

One of the most well-known ventilator distribution companies in Pakistan provided data for the data collection step. Years' worth of sales data from all regions and territories of Pakistan are included in the dataset, which has several factors. For this investigation, the actual sales data is essential.

3.2 Step 2:

To obtain information for additional analysis, data from 35 to 36 distribution centers were combined during the data processing stage. To simplify and remove extraneous variables from the dataset, over 100 product data points and thousands of transactions were integrated. To reduce the variable size and investigate the connection between ventilator sales and all other factors, a variety of methods are used [22].

3.2.1 Variable Identification

Numerous variables that both directly and indirectly affect ventilator distribution are present in the dataset. For this study, these data were taken out of the Oracle database [23]. There were upper and lower sections for each region. Local clinics, smaller medical supply stores, and direct consumers/customers make up the lower distribution area, whereas larger hospitals, large medical equipment suppliers, and institutional buyers make up the upper distribution area. First, the factors that were found in the data utilized for this study are as follows:

3.3 Step 3:

The process of cleaning, converting, and normalizing unprocessed data is known as data analysis. During the data analysis stage, problems including deleting redundant entries, managing null values, fixing negative values, and getting rid of extraneous variables are resolved to extract valuable information. The dataset used for this study has 265,000 rows, or transactions, about the distribution of ventilators, and more than 40 variables.

Normalization is putting the data in order and getting it ready for analysis. This involves organizing the facts in a way that makes sense and is easy to understand. The data is separated into several datasets according to parameters like year, location, and product type to make this easier. This division enables a thorough analysis of every scenario independently, guaranteeing a thorough comprehension of the distribution patterns and trends.

3.4 Step 4:

In this research, the graphical representation of data is drawn using different context plots, graphs, etc. Graphical analysis of data is a pictorial or tabular representation of data where the viewer can readily grasp the data flow by examining graphs and tables. Plots in this research illustrate the trend of ventilators to help with data comprehension. Some of the plots are seasonal, some are static, and some show both upward and decreasing patterns in sales. Before viewing the pictorial or graphical representation of data in various scenarios, we must first determine whether sales and other variables are correlated.

3.4.1 Correlation:

To assess the impact of ventilator distribution on various factors, we examine the correlation between each factor and the quantity of ventilators distributed. Variables that show negative correlations with ventilator distribution are excluded from the dataset.

3.4.2 Scatter Plots of variables:

The correlation between two factors about ventilator distribution was graphically represented using a scatter plot. As seen in Fig. 3, a scatter plot displays the data's visual distribution concerning another variable. The tighter the association or higher the correlation between the two variables, the closer the data points form a straight line when plotted. The variables are considered to have a positive correlation if the data points form a straight line that extends from close to the origin to high values on the y-axis. On the other hand, if the data points begin at high values on the y-axis and move toward low values, the variables have a negative association.

To see the trend of the variables used in this research on sales, check their scatter plot formed in Microsoft Excel sales on the y-axis of every graph:

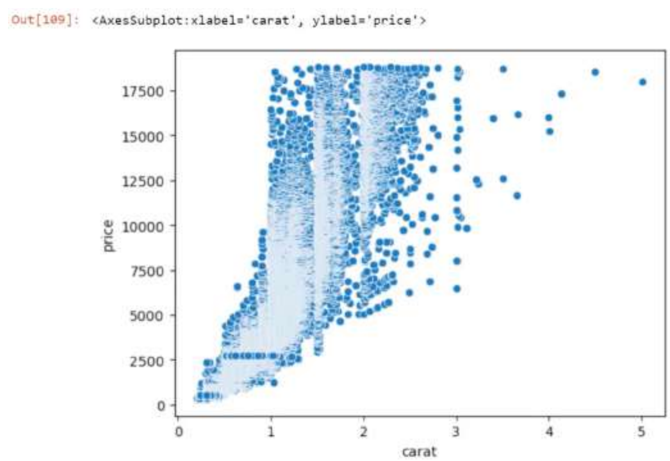

Figure 3. Scatter Plot Showing Correlation Between Two Variables in Ventilator Distribution

The foregoing definition indicates a positive correlation between sales and the number of ventilators supplied on credit, as demonstrated in Fig. 4. This relationship pertains to the quantity of ventilators distributed on credit and sales [23]. This indicates that the sales quantity rises when ventilators are supplied to dealers on a credit basis.

As per the definition given, the relationship between sales and the amount of returned ventilators is the correlation between the quantity of ventilator returns and sales. A perfect negative association is found between the number of ventilators sold and the number of ventilators returned, as Fig. 5 illustrates.

As illustrated in Fig. 6, the line plot displays the frequency of sales concerning place; a company's de-

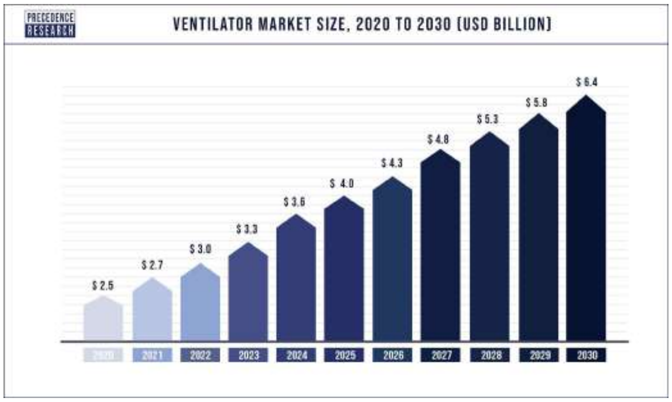

Figure 4. Relationship Between Credit Supply and Ventilator Sales

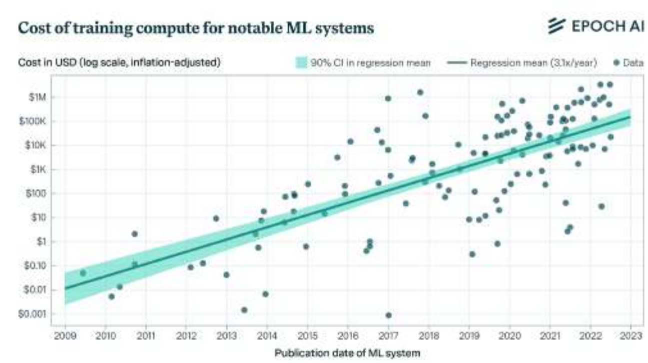

Figure 5. Relationship Between Ventilator Sales and Return

pot (location) is plotted on the x-axis. The company's sales by location are displayed in this graph. For convenience, the firm has assigned unique codes to each site. The sales data displayed in this graph indicate that the initial depot had higher sales, ranging from 300 to 320. The state location has large cities, which explains why sales are high here.

As shown in Fig 7, the boxen plot shows the sale frequency concerning location; on the x-axis and the y-axis, there is the depot of a company (location). This graph shows the company's location-wise sales. All the locations are called by specific codes given by a company for their ease. This graph shows that the sales of different locations show the highest sales in the starting depot between 300 and 320. There are big cities in the state location, so sales are high here. In contrast. These are small cities with a smaller population than big cities, therefore, ventilator usage is lower here than

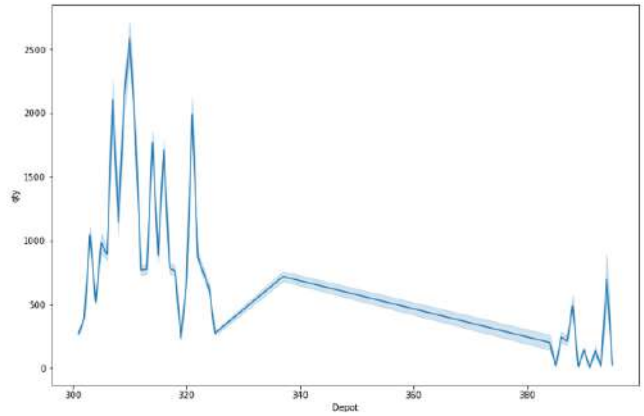

Figure 6. Sales Distribution by Location Using Line Plot

in other big cities.

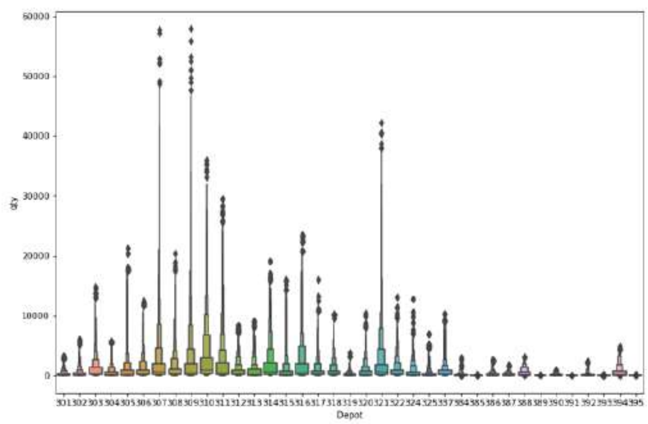

Figure 7. Location-Based Sales Distribution Using Boxen Plot

The boxen plot, as displayed in Fig. 8, shows the distribution frequency of ventilators based on various models; the model code of the ventilators is represented on the y-axis, which is plotted on the x-axis. The distribution frequency of different ventilator models by a company is seen in this graph. For ease of use, the firm assigns a unique code to each ventilator model. For example, 101001 corresponds to the VENT-1000 BASIC MODEL, 101002 to the VENT-2000 ADVANCED MODEL, 101003 to the VENT-3000 ELITE MODEL, 101004 to the VENT-4000 PRO MODEL, and so on. The distribution frequency of these ventilator models is displayed on this graph. The demand for particular ventilator types, which are used in a variety of healthcare settings, may be seen in the sales data for different models.

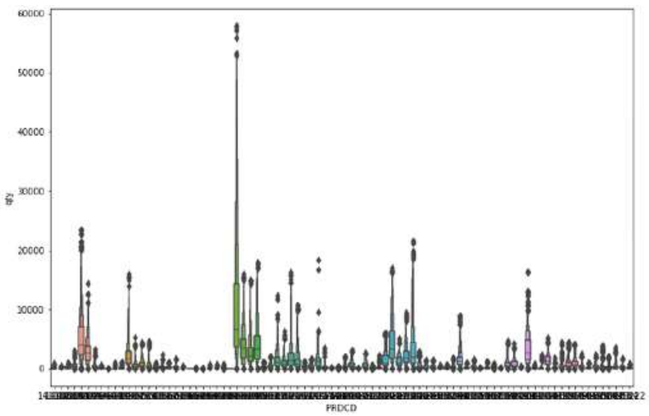

Figure 8. Ventilator Model Sales Distribution Using Boxen Plot

3.4.3 Location-Wise Product Sale:

Location-wise sales show the graphical representation of all products in multiple locations to check their sales value.

3.4.4 Pakistan Model Wise Sale

As shown in Fig 9, the line plot shows the sale frequency for the model; on the x-axis, there are sales, and on the y-axis, there is the model code of the company. This graph shows the company's model-wise sales, specifically in Pakistan. This graph shows the sales of the different models.

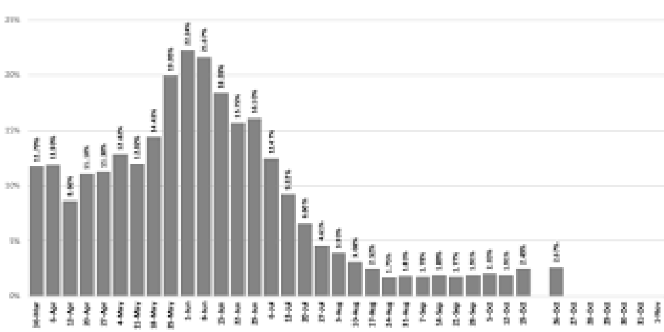

Figure 9. Model-Wise Sales in Pakistan Using Line Plot

3.5 Step 5

Data sampling for the ventilator distribution model is done in step five. The training data are incorporated into the model at this step. Data must pass through several compatibility tests or be further processed for refinement to be ready for model integration. The information used in this study includes more than two million ventilator distribution records. By removing important information and condensing the data size for better model performance, this data is incorporated into the model training process.

3.5.1 Data Clustering:

The data should be arranged by location and particular ventilator models in order to examine the impacts of ventilator sales across different product categories and geographical areas. Classify the data first by region, including Karachi, Lahore, Faisalabad, Peshawar, Hyderabad, Quetta, and other places. Gather sales information for various ventilators kinds for every area. Sort the data next according to the models of ventilators, for example, Type A Model 1, Type A Model 2, Type B Model 1, and so forth. Add categories such as high-frequency ventilators, non-invasive ventilators, and portable ventilators as well. Integrate the product-specific data with the location-based sales data for a thorough study that assesses sales performance and trends across various ventilator kinds and geographies.

3.5.2 Regression Analysis:

A dependent variable and (one or more) independent variable(s) are estimated using regression analysis. It is a collection of statistical techniques intended to calculate the correlation between one or more independent and dependent variables. Additional linear regression analysis can be used to analyze ventilator distribution like that of a simple linear model but with the addition of additional independent variables. For example, a variety of factors, including population density, infection rates, ICU capacity, and the availability of medical staff, may affect the number of ventilators required at various hospitals (dependent variable). Therefore, we can model how these variables affect the demand for ventilators with the aid of multiple linear regression.

Table 1 shows the output summary of the regression statistics, and Table 2 shows the regression results. The mathematical representation of multiple linear regression is:

$$Y = a + b_{x1} + c_{x2} + d_{x3} + \epsilon \quad (1)$$

Where:

- Y – Dependent variable
- X1, X2, X3 – Independent (explanatory) variables
- a – Intercept
- b, c, d – Slopes
- Epsilon– Residual (error)

Table 1. OUTPUT SUMMARY of REGRESSION STATISTICS

Regression Statistics	Outputs
Multiple R	0.961%
R Square	0.92352%
Adjusted R Square	0.923508%
Standard Error	669.6915%
Observations	100744%

Table 2. Regression Results

Variable	Coefficient	Std. Error	t-Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	9.804	2.425	4.042	5.29E-05	5.051	14.558	5.051	14.558
X Variable 1	1.138	0.013	85.224	0	1.111	1.164	1.111	1.164
X Variable 2	-0.686	0.016	-43.720	0	-0.717	-0.656	-0.717	-0.656
X Variable 3	4.476	0.023	192.021	0	4.430	4.521	4.430	4.521
X Variable 4	-0.333	0.172	-1.933	0.053	-0.671	0.005	-0.671	0.005
X Variable 5	0.548	0.061	8.994	2.42E-19	0.428	0.667	0.428	0.667
X Variable 6	-0.550	0.003	-205.35	0	-0.555	-0.545	-0.555	-0.545
X Variable 7	1.277	0.034	37.394	0	1.210	1.344	1.210	1.344
X Variable 8	-0.719	0.033	-21.824	2.4E-105	-0.783	-0.654	-0.783	-0.654
X Variable 9	0.460	0.042	11.042	2.49E-28	0.379	0.542	0.379	0.542
X Variable 10	3.310	0.411	8.055	8E-16	2.505	4.115	2.505	4.115
X Variable 11	0.418	0.326	1.283	0.1996	-0.220	1.056	-0.220	1.056
X Variable 12	0.007	0.000	43.257	0	0.007	0.008	0.007	0.008
X Variable 13	0.284	0.001	278.458	0	0.282	0.286	0.282	0.286
X Variable 14	0.298	0.001	280.740	0	0.296	0.300	0.296	0.300
X Variable 15	0.083	0.002	41.815	0	0.079	0.087	0.079	0.087
X Variable 16	0.228	0.003	83.458	0	0.223	0.234	0.223	0.234

3.5.3 Multiple R

This is the correlation coefficient. This tells you how strong the linear relationship is. For example, a value of 1 indicates a perfect positive relationship and a value of zero means no relationship at all. This is the square root of r squared. In this analysis, the multiple r is 0.961; therefore the relationship is strong.

3.5.4 R squared

This is r2, the Coefficient of Determination. This tells you how many points fall on the regression line. For example, 80% indicates that 80% of the variation in y-values around the mean is explained by the x-values. That is, 80% of the values fit the model. The R-squared value is 0.92352, which means 92.35%, so 92.3% of the values fit the model.

3.5.5 Adjusted R square

The adjusted R-square adjusts for the number of terms in the model. If you have more than one x variable you'll want to use this instead of 2. The Adjusted R-square of 0.923508 means that 92.3% of the value fits the model.

3.5.6 Standard error of regression

An estimate of the standard deviation of the error. This is not the same as the standard error in descriptive statistics. The standard error of the regression is the precision of the regression coefficient measured. If the coefficient is large compared to the standard error, then the coefficient is probably different from 0.

3.6 Step 6

As seen in Fig 10, in step six, we constructed a ventilator distribution prediction model after transforming the data into a certain format. Using an Artificial Neural Network (ANN), a prediction model was created during this research step. A computational model called an Artificial Neural Network (ANN) aims to mimic how nerve cells in the human brain function. It processes and adapts to incoming data automatically via a learning algorithm, mimicking the way the human brain perceives and processes data. Because of this, ANNs are very useful for modeling non-linear statistical data, such as ventilator distribution prediction. The input layer, hidden layers, and output layer are the three interconnected layers that make up an Artificial Neural Network (ANN). Neurons make up the input layer; they take information, process it, and then transmit the finished product to the output layer, which is made up of deeper buried layers. The adaptive transformation of the data acquired from one layer to the next is the job of the hidden layers. By acting as both an input and an output layer, each layer gives the ANN the ability to represent increasingly intricate patterns and relationships in the data. These inner layers are collectively known as the neural layers.

Though there are many benefits to an ANN, its capacity to learn from observational data sets is perhaps the most well-known. As a result, ANNs have been employed as instruments for approximating random functions. These tools assist in defining logistical functions or distributions and in estimating the most economical and optimal ways to distribute ventilators. To find solutions, ANNs analyze data samples as opposed to complete data sets, which saves time and resources. ANNs are thought of as straightforward mathematical models that improve on current data analysis tools. They can be used in a variety of real-world contexts, including supply chain efficiency, demand forecasting in emergencies, and ventilator distribution optimization in response to healthcare needs.

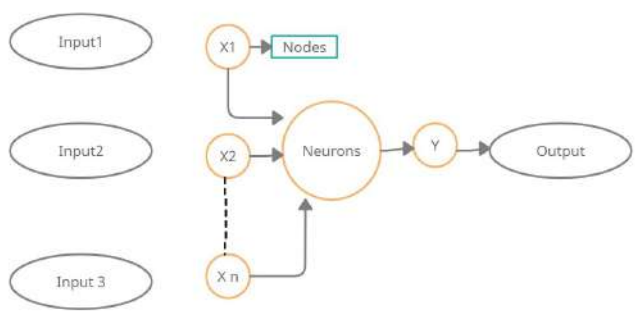

Figure 10. Ventilator Distribution Prediction Model Using Artificial Neural Network (ANN)

3.6.1 Input Layer:

It accepts input data in different formats (text, float, integer, etc)provided by the programmer.

3.6.2 Hidden Layer:

The hidden layer is present between the input and output layers. It performs all the calculations to find hidden features and patterns.

3.6.3 Output Layer:

The input goes through a series of transformations using the hidden layer, which finally results in an output that is conveyed using this layer [24].

3.7 ANN Model Building:

We first created the model's layers and supplied input to the input layer by adding the pertinent independent variables before constructing the ventilator distribution model. These variables may include the demographics of the patients, the needs of the medical facility, and local health information. After processing this data, the hidden layer makes predictions about the distribution and allocation of ventilators. The dataset's independent variables were all used as inputs to guarantee thorough research and precise forecasts for the efficient distribution of ventilators.

The input vector representing different parameters (like demand forecasts, inventory levels, and delivery schedules) is presented to the network during the supervised learning step of the ANN model training for ventilator distribution. This produces an output vector (like predicted distribution quantities and optimal allocation). The intended output vector—that is, the best distribution strategy based on actual needs—is then contrasted with this output vector. If there is a difference between the intended and actual output vectors, an error signal is produced. The network's weights are iteratively modified based on this error signal until the actual output matches the intended distribution targets [25].

4 Analysis of Result

4.0.1 Model Summary

The table 3 below shows the results of the model.

4.0.2 Model Accuracy

As shown in Fig 11, the final accuracy is 90% which is remarkable for Artificial Neural Network (ANN).

5 Results

The accuracy of the model was approximately 90%, which is a good neural network model. To make this more accurate, we need to further refine the data with another process. Thus the research hypothesis of this study is 90% true that the independent variable 90% impacts ventilator sales.

Table 3. Model Summary

Layer (type)	Output Shape	Param #
dense_20 (Dense)	(None, 20)	40
dense_21 (Dense)	(None, 20)	420
dropout_8 (Dropout)	(None, 20)	0
dense_22 (Dense)	(None, 10)	210
dropout_9 (Dropout)	(None, 10)	0
dense_23 (Dense)	(None, 5)	55
dense_24 (Dense)	(None, 1)	6
Total params:	**731**	
Trainable params:	**731**	
Non-trainable params:	**0**	

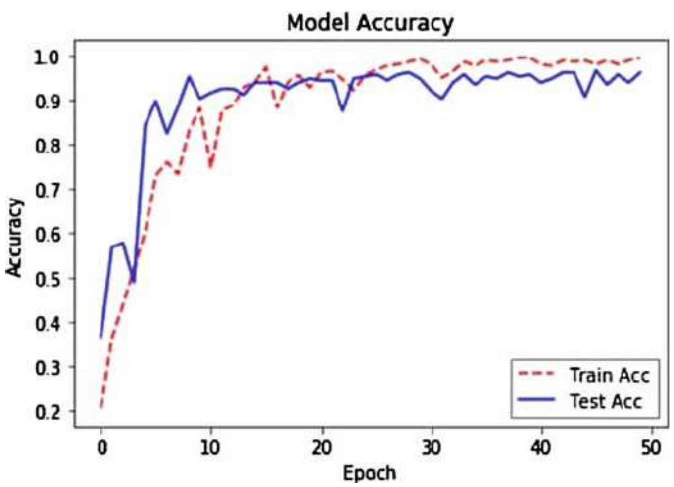

Figure 11. Accuracy of The Proposed Model

6 Conclusion and Future Work

According to the ANN model, the records of ventilator distribution firms are used to predict their products. The accuracy of the results was found to be 90%. However, due to variables like disease outbreaks or climatic change, its accuracy may vary seasonally. Model correctness must be assessed using datasets from particular periods or comparable circumstances to handle uncommon cases. This paper presents a particular predictive technique based on sales data that employs an Artificial Neural Network (ANN); every variable is used to improve the model's performance. Furthermore, this study shows that, in the context of ventilator distribution, independent variables can play a major role in the efficient model-building process for prediction and optimization.

The goal of this research is to minimize expenses related to inventory management, transportation, and purchasing to optimize the ventilator distribution process. Our goal was to offer a workable answer to this problem. Predicting ventilator inventory levels, controlling shortages, and preventing excess inventory are all part of the research's stated problem. An Artificial Neural Network (ANN) model trained using a dataset from ventilator distribution businesses produced an accuracy of 90%, which is good for early prediction. Nevertheless, the model was made more general by eliminating certain factors and refining the input layer's input variables using a smaller, filtered dataset obtained through sensitivity analysis.

An additional model might be created to evaluate the efficacy of ventilator distribution concerning disease outbreaks or seasonal demand. The dataset has been partitioned into clusters, which correspond to distinct cities and ventilator kinds. We used an Artificial Neural Network (ANN) to analyze data from each year independently to assess the effectiveness of this model. To verify correctness, this can be done by comparing data from previous years with the distribution metrics from the current year.

In future work, more extensive datasets with additional characteristics like seasonal fluctuations and regional disease outbreaks can be used to further optimize the existing Artificial Neural Network (ANN) model. This will increase the accuracy of the prediction, especially when there is erratic demand because of pandemics or catastrophes. A further way to improve the accuracy of the model is to incorporate clustering approaches based on data particular to cities and ventilator models. The ANN model can also be cross-validated using previous data to continuously evaluate and enhance its performance. This allows it to be trained on larger datasets, accounting for real-time data spanning numerous years.

Author Contributions

Mohsin Mubeen Abbasi: Conceptualization, Methodology, Software **Syed Muhammad Daniyal**: Data curation, Writing- Original draft preparation. **Abdul Ahad**

Abro: Supervision. **Dilbar Hussain**: Visualization, Investigation. **Usama Amjad**: Software, Validation. **Noman Bin Zahid**: Writing- Reviewing and Editing.

Compliance with Ethical Standards

It is declared that all authors don't have any conflict of interest. It is also declared that this article does not contain any studies with human participants or animals performed by any of the authors. Furthermore, informed consent was obtained from all individual participants included in the study.

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