

PROFESSIONAL TRAINING REPORT

Sathyabama Institute of Science and Technology (Deemed to be University)

Submitted in partial fulfilment of the requirements for the award
of Bachelor of Technology Degree in Information Technology

By

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DEPARTMENT OF INFORMATION TECHNOLOGY

SCHOOL OF COMPUTING

SATHYABAMA

**INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)**

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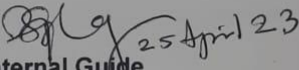
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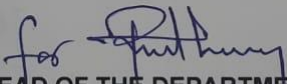
DEPARTMENT OF INFORMATION TECHNOLOGY

BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **R. JAYASRI** who carried out the project entitled "**CUSTOMER PRODUCT COUNT**" under my supervision from March 2023 to April 2023.

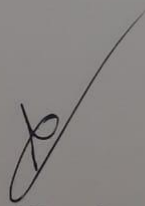

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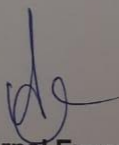
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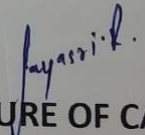

External Examiner

DECLARATION

I JAYASRI.R hereby declare that the Project Report entitled "**CUSTOMER PRODUCT COUNT**" done by me under the guidance of Dr.G.MATHIVANAN M.E.,Ph.D., at Sathyabama Institute of Science and Technology (Deemed to be University), Jeppiaar Nagar, Rajiv Gandhi Salai, Chennai - 600119 is submitted in partial fulfillment of the requirements for the award of Bachelor of Technology degree in Information Technology.

DATE: 25/04/2023

PLACE: CHENNAI


SIGNATURE OF CANDIDATE

Certificate:



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ABSTRACT

Predicting future customer behavior provides key information for efficiently directing resources at sales and marketing departments. Such information supports planning the inventory at the warehouse and point of sales, as well strategic decisions during manufacturing processes. In this paper, we develop advanced analytics tools that predict future customer behavior in the noncontractual setting. We establish a dynamic and data driven framework for predicting whether a customer is going to make purchase at the company within a certain time frame in the near future. For that purpose, we propose a

new set of customer relevant features that derives from times and values of previous purchases. These customer features are updated every month, and state of the art machine learning algorithms are applied for purchase prediction. In our studies, the gradient tree boosting method turns out to be the best performing method. Using a data set containing more than 10 000 customers and a total number of 200 000 purchases we obtain an accuracy score of 89% and an AUC value of 0.95 for predicting next moth purchases on the test data set.

On the basis of a performance evaluation, a best suited predictive model is suggested for the sales trend forecast. The results are summarized in terms of reliability and accuracy of efficient techniques taken for prediction and forecasting. We will also explore how such data can be used to obtain insights into consumer behavior, and the impact of such data on organizational forecasting. These issues could be overcome by using various data mining techniques. In this paper, we briefly analyzed the concept of sales data and sales forecast. The various techniques and measures for sales predictions are described in the later part of the research work.

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CHAPTER-1

INTRODUCTION

Sales forecasting is a crucial business exercise. Accurate sales forecasts allow business leaders to make smarter decisions about things like goalsetting, budgeting, hiring, and other things that affect cash flow. A sales forecast is a prediction of future sales revenue. Sales forecasts are usually based on historical data, industry trends, and the status of the current sales pipeline. Businesses use the sales forecast to estimate weekly, monthly, quarterly, and annual sales totals. Sales forecasting is also different from sales goal-setting. While a sales goal describes what you want to happen, a sales forecast estimates what will happen, regardless of your goal. Sales prediction is playing creating and noteworthy employment in various fields, for instance, money related envisioning, electric power deciding, resource conjecture, etc.

Arrangements conjecture is a noteworthy basic for enormous business orchestrating and right powerful, allowing associations to all the more promptly structure their business works out. Sales prediction is critical for separated associations, especially vehicle arrangements, land, and other customary undertakings. The desires are generally done by applying verifiable systems, for instance, backslide or the autoregressive–moving-typical (ARMA) taking into account recorded arrangements data.

Regardless, these procedures simply work for explicit data. Such enormous quantities of components with complex interrelationships sway bargains and in all likelihood consolidate ones with a sensible degree of defencelessness. Using data mining, we can perceive potential models and headway consistency from most of the data. As needs are, a growing number of researchers revolve around how to use data mining to process recorded data and handle inclines in bargains desire.

1.1 FORECASTING

Forecasting is the process of projecting past sales demand into the future. Implementing a forecasting system enables you to assess current market trends and sales quickly so that you can make informed decisions

about the operations. It is a planning tool that enables businesses to chart their next moves and create budgets that will hopefully cover whatever uncertainties may occur.

1.1.1 Types of Forecasting

- Quantitative
- Qualitative

1.2 SALES FORECASTING

Sales forecasting is a prediction of future sales revenue and Sales forecasts are usually based on historical data, industry trends, and the status of the current sales pipeline. Businesses use the sales forecast to estimate weekly, monthly, quarterly, and annual sales totals. Just like a weather forecast, your team should view your sales forecast as a plan to work from, not a firm prediction. Sales forecasting is also different from sales goal-setting. While a sales goal describes what you want to happen, a sales forecast estimates what will happen, regardless of your goal. They can also help enterprises to plan their marketing and advertising efforts. Sales forecasting can help businesses make informed decisions about allocating resources. Sales forecasting is not an exact science, and uncertainty is always involved. However, sales forecasts can give businesses a good idea of what to expect in the future and help them plan accordingly.

1.2.1 Pros and Cons Pros:

- i) Provides insights into upcoming sales and revenue.
- ii) Appeals to stakeholders.
- iii) Aligns business strategies and result.
- iv) Provides opportunities to make adjustments.
- v) Reveals patterns in data.
- vi) Helps integrate lead sources.
- vii) Begins gathering data on new products or services.
- viii) Establishes a sales process.

Cons:

- i) Is hard to predict.
- ii) Creates biased opinions.
- iii) Requires clean data.
- iv) Requires time.
- v) Lacks essential details with numerical data.
- vi) Affected by employee turnover.
- vii) Promotes false optimism.

1.3 SALES PREDICTION

Sales prediction also commonly called sales forecasting is the process of estimating future sales by predicting the amount of product or services an individual salesperson, a sales team, or a company is likely to sell in a fixed time period i.e., next week, month, quarter, or year.

There are a lot of different methods for predicting sales, but the important thing is that they're all backed by some kind of data. Sales prediction allows you to replace gut feelings with evidence-based decision-making.

1.3.1 Benefits of Sales Prediction:

- Set better goals
- Evaluate sales performance
- Plans effectively
- Makes decision with confidence

1.4 DATA PROCESSING:

The influencing factors of sales from five aspects: product attributes, merchant attributes, buyer attributes.

1.4.1 Product Attributes:

The characteristics of the product itself are the main factors affecting the sales volume. The product attribute indexes finally determined in this paper are as follows: price quality grade, collection volume.

1.4.2 Merchant Attributes:

The characteristics of businesses through the attributes of business time store level, sales volume and score. The “scoring” index includes the scoring results of “product description consistency score,” “logistics service level score,” and “comprehensive service score”.

1.4.3 Buyer Attributes:

The basic information of customers, such as gender, age, education, information of products purchased, and online transaction amount, involves personal privacy issues, there is no channel for obtaining it on major ecommerce platforms. Therefore, this paper selects buyer loyalty to reflect customers’ satisfaction with products and their personal consumption preferences.

1.5 SPECIFICATIONS

1.5.1 Hardware Configuration

- Processor - I5
- Speed- 3 GHz
- RAM - 8GB (min)
- Hard Disk - 500 GB
- Key Board - Standard Windows Keyboard
- Mouse - Two or Three Button Mouse
- Monitor - LCD

- Ethernet connection :(LAN)

1.5.2 Software Configuration

- Microsoft Excel sheet
- Power BI Application
- Web Browser

CHAPTER - 2

LITERATURE SURVEY

2.1 AN APPROACH OF SALES PREDICTION SYSTEM OF CUSTOMERS USING DATA ANALYTICS TECHNIQUES

In country there are lots of supermarkets, shopping malls the managing sales of the shopping malls is very exigent works. The customer requirements will be changed every month, the manager or store owners are facing the problem for keeping stock for upcoming months. In this work we proposed data analytics-based approach for predicting the sales details based on the last 12 months data and it will generate report, in which moth maximum products are sales profit of the each and every month. This system performs various task like, finding best months for sales, calculate monthly earned money from different products, which city sold the maximum products, when will be the best time for advertisement to maximum customer to buy the products also generates report, which are items are frequently bought by the customer to keep stock for upcoming months and, increase the profit of the shopping mall business. A Sales analysis is very important constraint to run any business Successful.The prediction of customers purchased item is playing important role in Sales Analysis, In this proposed work subsequent task are implemented using python coding like data analysis such as best month for sales, best month for earned more,city sold more product, best time for advertisement to maximize the likelihood of customer buying product ,products are purchased by together finally what product are sold more reason behind of selling more based on the Sales Dataset.

2.2 A survey on retail sales forecasting and prediction in fashion market

This paper conducted an overview of recent progress in the field of sales forecasting with the focus on fashion and new product sales forecasting. Conventional forecasting methods face challenges in producing accurate sales data for new products and consumer-oriented goods. In particular, uncertain demand, seasonality, product variability as well as a lack of historical can hardly be handled. Within the recently introduced approaches, hybrid forecasting models perform more precisely. Moreover, this study gave an overview of the literature focusing on the predictive value of user-generated content and search queries. For future work, different aspects of fashion forecasting can be followed: Most reviewed works propose complex models in order to produce precise forecasts, and validate them in most cases with real sales data. However, still fashion companies face challenges in adapting these complex models. Therefore, one interesting aspect is to explore models which are accurate and at the same time applicable for the daily work of fashion companies. Furthermore, it is worth to focus more on the diverse impacting factors which have been described. Different aspects such as the general handling and the reduction possibilities on the forecast results can be examined. Finally, the measurement of the predictive value of user-generated content in real life is a valuable aspect, which is currently followed and explored by the authors of this review.

2.3 Forecasting Sales Profiles of Products in an Exceptional Context: COVID-19 Pandemic

The fashion industry is one of the economic sectors that were seriously impacted by the COVID-19 pandemic. Existing sales forecasting systems have become inapplicable due to the remarkable change in consumer purchasing behaviors, which has left retailers in a situation where they have to rapidly act to deal with the new environment's constraints. Motivated by a real business project, this study proposed a new sales forecasting methodology that can be applied in such an exceptional context—the COVID-19 pandemic, where train and test datasets present different constraints. Our proposed methodology suggests starting with a normal, yet advanced, sales forecasting

system as if there is no additional constraint for the test set—2020's sales. For this purpose, we used a clustering procedure, applied to cumulative sales profiles, that aims to identify k different sales prototypes, followed by a RF classifier that assigns the corresponding sales prototype for each new item based on its characteristics. Thereafter, once normal predictions are obtained, a regression approach is proposed to model the crisis' impact on sales and correct the predictions accordingly. The proposed correction model is optimized within the time window made up of the few weeks following the start of the crisis, where real sales (affected by the pandemic) and previously predicted sales are available. By analyzing sales behaviors in this window, and optimizing the regression models' parameters, the proposed model is able to predict an optimal correcting coefficient capable of correcting the predicted sales for the next weeks (short-term prediction). We tested the proposed methodology on four different datasets of online sales corresponding to four different families of products. The results showed that we were able to correct sales predictions on the desired period (four weeks) in an efficient way for all of the datasets. Hence, our proposed framework has offered an effective tool to our fashion retailer partner to better manage his supply chain, by knowing which items from the previous collection must be kept in stores, and which new items must be supplied to stores after the end of the lockdown period

2.4 Predicting Online Product Sales using Machine Learning

Product sales prediction is a major aspect of purchasing management. One of the key challenges faced nowadays by organizations the dynamic, international and unpredictable business environment in which they operate. With growing customer expectations for price and quality, manufacturers today can no longer rely only on cost advantage that they have over their rivals. Forecasting the sales are crucial in determining inventory stock levels and accurately estimating the future demand for goods has been an ongoing challenge in industries. If goods are not readily available or if goods availability is more than demand overall profit can be compromised. As a result, sales prediction for goods can be significant to ensure that loss is

minimized. Depending on this study, our project is creating a prediction model using machine learning algorithms for accurately predicting online product sales. Our project aims to use up-to-date data which includes online reviews, online ratings, online promotional strategies and sentiments and various other parameters for predicting product sales.

2.5 Prediction of Merchandise Sales on E-Commerce Platforms Based on Data Mining and Deep Learning

Online business has grown exponentially during the last decade, and the industries are focusing on online business more than before. However, just setting up an online store and starting selling might not work. Different machine learning and data mining techniques are needed to know the users' preferences and know what would be best for business. According to the decision-making needs of online product sales, combined with the influencing factors of online product sales in various industries and the advantages of deep learning algorithm, this paper constructs a sales prediction model suitable for online products and focuses on evaluating the adaptability of the model in different types of online products. In the research process, the full connection model is compared with the training results of CNN, which proves the accuracy and generalization ability of CNN model. By selecting the non-deep learning model as the comparison baseline, the performance advantages of CNN model under different categories of products are proved. In addition, the experiment concludes that the unsupervised pretrained CNN model is more effective and adaptable in sales forecasting. The analysis results show that CNN model has good prediction accuracy and generalization ability and is suitable for sales prediction of online products in different industries. For the problem that the samples show a long tail distribution, although it does not significantly affect the training results of the model, in practical application, enterprise resources can be used to expand data sources.

CHAPTER – 3

METHODS &ALGORITHM USED

3.1 PROJECT DEVELOPMENT:

In this section, there is an overview of the process of data mining and data modelling, from collecting the data, through the data preparation and finally the data modeling. Data cleaning and formatting can be considered as the most critical part of the whole project according to several data scientists. Figure 3.1 shows how the process of data mining works to extract knowledge using algorithms.

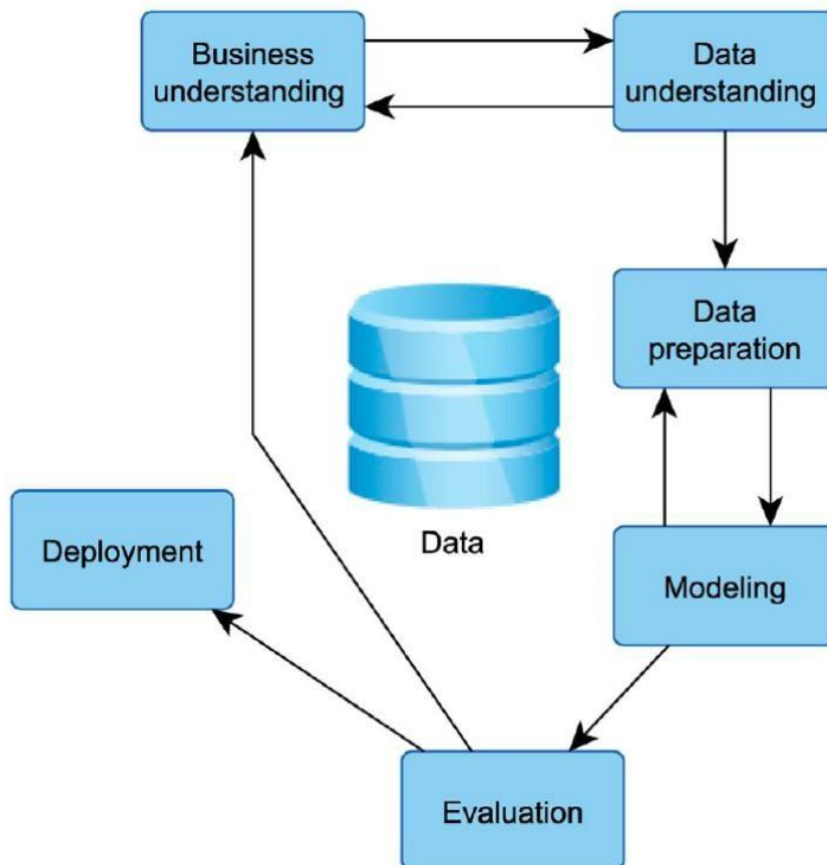


Fig:3.1 Project Development

3.2 DATA ANALYTICS:

The process of data analysis, or alternately, data analysis steps, involves gathering all the information, processing it, exploring the data, and using it to find patterns and other insights. The process of data analysis consists of: Data

Requirement Gathering: Ask yourself why you're doing this analysis, what type of data you want to use, and what data you plan to analyse.

3.2.1 Data Collection:

Guided by your identified requirements, it's time to collect the data from your sources. Sources include case studies, surveys, interviews, questionnaires, direct observation, and focus groups. Make sure to organize the collected data for analysis.

3.2.2 Data Cleaning:

Not all the data you collect will be useful, so it's time to clean it up. This process is where you remove white spaces, duplicate records, and basic errors. Data cleaning is mandatory before sending the information on for analysis.

3.2.3. Data Analysis:

Here is where you use data analysis software and other tools to help you interpret and understand the data and arrive at conclusions. Data analysis tools include Excel, Python, R, Looker, Rapid Miner, Charito, Meta base, Rehash, and Microsoft Power BI.

3.2.4. Data Interpretation:

Now that you have your results, you need to interpret them and come up with the best courses of action based on your findings.

3.2.5. Data Visualization:

Data visualization is a fancy way of saying, "graphically show your information in a way that people can read and understand it." You can use charts, graphs, maps,

bullet points, or a host of other methods. Visualization helps you derive valuable insights by helping you compare datasets and observe relationships.

3.3 Types of Data Analysis:

The four types of data analysis are:

1. Descriptive Analysis
2. Diagnostic Analysis
3. Predictive Analysis
4. Prescriptive Analysis

3.3.1. DESCRIPTIVE ANALYSIS:

Descriptive analytics answer the question, “What happened?”. This type of analytics is by far the most commonly used by customers, providing reporting and analysis centered on past events. It helps companies understand things such as:

- How much did we sell as a company?
- What was our overall productivity?
- How many customers churned in the last quarter?

Descriptive analytics is used to understand the overall performance at an aggregate level and is by far the easiest place for a company to start as data tends to be readily available to build reports and applications. It’s extremely important to build core competencies first in descriptive analytics before attempting to advance upward in the data analytics maturity model. 23 Core competencies include things such as data modeling fundamentals, communicating data with right visualization and basic dashboard skills. It’s likely you’ve adopted some form of descriptive analytics internally, whether that be static P&L statements, PDF reports, or reporting within an analytics tool. For a true descriptive analytics program to be implemented, the concepts of repeatability and automation of tasks must be top of mind. Repeatability in that a data process is standardized and can be regularly applied with minimal effort (think a weekly sales report), and automation in that complex task (VLOOKUPS, merging of excel spreadsheets, etc.) are automated—requiring little to no manual intervention.

3.3.2. DIAGNOSTIC ANALYSIS:

Diagnostic analytics, just like descriptive analytics, uses historical data to answer a question. But instead of focusing on “what”, diagnostic analytics addresses the critical question of why an occurrence or anomaly occurred within your data. Diagnostic analytics also happens to be the most overlooked and skipped step within the analytics maturity model. Anecdotally, I see most customers attempting to go from “what happened” to “what will happen” without ever taking the time to address the “why did it happen” step. This type of analytics helps companies answer questions such as:

- Why did our company sales decrease in the previous quarter?
- Why are we seeing an increase in customer churn?
- Why is a specific basket of products vastly outperforming their prior year sales figures? Diagnostic analytics tends to be more accessible and fit a wider range of use cases than machine learning/predictive analytics. You might even find that it solves some business problems you earmarked for predictive analytics use cases. Being at the diagnostic analytics phase likely means you’ve adopted a modern analytics tool. Most modern analytics tools contain a variety of search-based, or lightweight artificial intelligence capabilities. ²⁴ These features allow for detailed insights a layer deeper (for example: the Key Drivers visualization in Power BI, or Qlik’s search-based insight functionality). To be clear, these are an effective lightweight means to address diagnostic analytics use cases but are not a means to a full-scale implementation. Software vendors like Sisu have built their core business around addressing diagnostic analytics use cases (what they call “augmented analytics”) and are a great bet. Diagnostic analytics is an important step in the maturity model that unfortunately tends to get skipped or obscured. If you cannot infer why your sales decreased 20% in 2020, then jumping to predictive analytics and trying to answer “what will happen to sales in 2021” is a stretch in advancing upward in the analytics maturity model.

3.3.3. PREDICTIVE ANALYSIS:

Predictive analytics is a form of advanced analytics that determines what is likely to happen based on historical data using machine learning. Historical data that comprises the bulk of descriptive and diagnostic analytics is used as the basis of building predictive analytics models. Predictive analytics helps companies address use cases such as:

- Predicting maintenance issues and part breakdown in machines.
- Determining credit risk and identifying potential fraud.
- Predict and avoid customer churn by identifying signs of customer dissatisfaction. At the outset of any predictive analytics build, three core elements need to be established:

- Identify a problem to solve,
- Define what is you want to predict, and

- State what you will achieve by doing so. To start you should collect existing data, organize data in a useful way to allow for data modeling, cleanse your data and review overall quality, and finally determine your modeling objective. 25 While modeling takes up the spotlight in predictive analytics, data prep is a crucial step that needs to happen first. This is why organizations with a rock-solid foundation in descriptive and diagnostic analytics are better equipped to handle predictive analytics. Simply put, the time and effort to prep, transform, and ensure data quality for retrospective reporting has already taken place. The groundwork should be relatively well laid to quickly identify and leverage data for the modeling phase. I always encourage customers with well-defined KPIs and business logic in a specific business reporting area (think sales reporting for example) to use that as the first predictive analytics use case. The goal is to derive value quickly, and there is no

better place to start than an area where you know data is well defined and of high quality.

3.3.4. PRESCRIPTIVE ANALYSIS:

Prescriptive analytics is the fourth and final pillar of modern analytics. Prescriptive analytics pertains to true guided analytics where your analytics is prescribing or guiding you toward a specific action to take. It is effectively the merging of descriptive, diagnostic, and predictive analytics to drive decision making. Existing scenarios or conditions (think your current fleet of freight trains) and the ramifications of a decision or occurrence (parts breakdown on the freight trains) are applied to create a guided decision or action for the user to take (proactively buy more parts for preventative maintenance). Prescriptive analytics requires strong competencies in descriptive, diagnostic, and predictive analytics which is why it tends to be found in highly specialized industries (oil and gas, clinical healthcare, finance, and insurance to name a few) where use cases are well defined. Prescriptive analytics help to address use cases such as:

- Automatic adjustment of product pricing based on anticipated customer demand and external factors.

- Flagging selects employees for additional training based on incident reports in the field. 26 Prescriptive analytics' primary aim is to take the educated guess or assessment out of data analytics and streamline the decisionmaking process. Prescriptive analytics is commonly considered the merging of descriptive, diagnostic, and predictive analytics. Getting started isn't so much a step-by-step list but rather the time and effort up front to build your competencies within the analytics maturity curve. Simply put, there is no starting point in prescriptive analytics without the requisite first three pillars of modern analytics being established first. If you're ready for prescriptive analytics, then quantifying your call to action and the underlying criteria will be the first requirement. For example: if the use case is to call corrective action for an employee (i.e. – additional training based on poor performance) then the factors that necessitate this action must be firmly established and the action itself

must be clearly defined. Knowing how each kind of analytics helps you better understand your data and how to use it.

3.4 System Requirements:

3.4.1 Windows:

- Microsoft® Windows® 7/8/10 64-bit
- 4 GB RAM minimum, 8 GB RAM recommended
- 2 GB of available disk space minimum,
- 4 GB Recommended 500 MB for IDE + 1.5 GB for Android SDK and emulator system image
- 1280 x 800 minimum screen resolution

3.4.2 Mac:

- Mac® OS X® 10.10 Yosemite or higher, up to 10.14 macOS Mojave
- 4 GB RAM minimum, 8 GB RAM recommended
- 2 GB of available disk space minimum,
- 4 GB Recommended 500 MB for IDE + 1.5 GB for Android SDK and emulator system image

3.4.3 Linux:

- GNOME or KDE desktop - Tested on gLinux based on Debian.
- 64-bit distribution capable of running 32-bit applications
- GNU C Library glibc 2.19 or later 17
- 4 GB RAM minimum, 8 GB RAM recommended
- 2 GB of available disk space minimum.

3.5 POWER BI:

Power BI is an interactive data visualization software product developed by Microsoft with a primary focus on business intelligence. It is part of the Microsoft Power Platform. Power BI is a collection of software services, apps, and connectors that work together to turn unrelated sources of data into coherent, visually immersive, and interactive insights. Data may be input by reading directly from a database, webpage, or structured files such as spreadsheets, CSV, XML, and JSON. Microsoft Power BI is a business intelligence (BI) platform that provides nontechnical business users with tools for aggregating, analyzing, visualizing and sharing data. 27 Power BI's user interface is fairly intuitive for users familiar with Excel, and its deep integration with other Microsoft products makes it a versatile self-service tool that requires little upfront training. Users can download an application for Windows 10, called Power BI Desktop, and native mobile apps for Windows, Android and iOS devices. There is also Power BI Report Server for companies that must maintain their data and reports on premises. That version of Power BI requires a special version of the desktop app -- aptly called Power BI Desktop for Power BI Report Server.

3.5.1 Uses of POWER BI:

Microsoft Power BI is used to find insights within an organization's data. Power BI can help connect disparate data sets, transform and clean the data into a data model and create charts or graphs to provide visuals of the data. All of this can be shared with other Power BI users within the organization. The data models created from Power BI can be used in several ways for organizations, including the following:

- telling stories through charts and data visualizations;
- examining "what if" scenarios within the data;
- creating reports that can answer questions in real time and help with forecasting to make sure departments meet business metrics. Power BI can also provide executive dashboards for administrators or managers, giving management more insight into how departments are doing

3.6 METHODOLOGY:

The project is implemented in Microsoft excel and Microsoft power Bi.

- We need to collect the data set for our product, over a year or 365 days.
- So, we are creating a data set for our product
- That includes:
 1. Payment method
 2. Customer age
 3. Customer gender
 4. Monthly sales
 5. Product brand
 6. Price range
 7. Product colour
 8. Product defect
 9. Warrenty
 - 10.Location

Now enter the dataset in Microsoft excel sheet as per the date and month as show in the fig 3.2

Excel spreadsheet titled "DISHA DJ EXCEL - Excel" showing a list of data entries. The columns are labeled A through AF. The data includes names (e.g., EMI, CASH, CARD), genders (MALE, FEMALE), ages, phone numbers, and various status indicators (e.g., YES, NO, WEST, EAST, SOUTH, NORTH). The spreadsheet is displayed in the "Sheet1" tab.

Excel spreadsheet titled "DISHA DJ EXCEL - Excel" showing a list of data entries. The columns are labeled A through AF. The data includes names (e.g., EMI, CASH, CARD), genders (MALE, FEMALE), ages, phone numbers, and various status indicators (e.g., YES, NO, WEST, EAST, SOUTH, NORTH). The spreadsheet is displayed in the "Sheet1" tab.

ID	Name	Gender	Age	Brand	Price	Color	Defect	Location
320	EMI	21	MALE	4	REDMI	30000-40000	GREY	NO
321	CASH	30	MALE	4	REALME	15000-20000	BLACK	NO
322	CASH	21	MALE	4	REALME	20000-30000	RED	NO
323	EMI	25	MALE	6	OPPO	10000-20000	RED	NO
324	EMI	23	FEMALE	8	REDMI	40000-50000	BLUE	YES
325	EMI	41	MALE	8	OPPO	30000-35000	GREY	NO
326	EMI	21	MALE	4	REDMI	25000-40000	RED	NO
327	EMI	25	MALE	7	OPPO	15000-25000	BLUE	YES
328	EMI	33	FEMALE	8	REDMI	50000-75000	GREY	NO
329	EMI	25	MALE	5	SAMSUNG	70000-90000	BLUE	NO
330	EMI	21	MALE	7	VIVO	30000-40000	BLUE	NO
331	EMI	41	MALE	6	REDMI	15000-20000	BLUE	NO
332	EMI	21	MALE	7	REALME	20000-30000	GREY	NO
333	EMI	24	MALE	7	SAMSUNG	10000-25000	BLACK	NO
334	EMI	28	MALE	6	VIVO	40000-50000	BLUE	NO
335	EMI	41	MALE	6	OPPO	30000-35000	GOLD	YES
336	EMI	21	FEMALE	4	REDMI	25000-40000	RED	NO
337	EMI	28	MALE	4	OPPO	15000-25000	GOLD	YES
338	CARD	30	MALE	7	OPPO	50000-75000	BLUE	YES
339	EMI	26	MALE	2	REDMI	70000-90000	RED	NO
340	CASH	34	MALE	8	OPPO	30000-40000	RED	NO
341	EMI	29	MALE	7	OPPO	15000-20000	RED	NO
342	CARD	34	MALE	4	REALME	20000-30000	GREY	NO
343	CARD	41	FEMALE	4	REDMI	10000-25000	BLACK	NO
344	EMI	30	FEMALE	5	OPPO	40000-50000	BLUE	NO
345	EMI	41	FEMALE	2	OPPO	30000-35000	RED	NO
346	EMI	33	FEMALE	7	VIVO	25000-40000	GREY	NO
347	CASH	41	MALE	8	VIVO	15000-25000	GOLD	YES
348	EMI	41	FEMALE	2	OPPO	50000-75000	GREY	NO
349	CASH	34	MALE	4	SAMSUNG	70000-90000	BLUE	YES
350	EMI	34	MALE	8	OPPO	30000-40000	BLUE	NO
351	CASH	27	MALE	4	REDMI	15000-20000	GOLD	YES
352	CARD	26	MALE	7	REDMI	20000-30000	RED	NO
353	EMI	21	MALE	9	REDMI	10000-25000	BLUE	NO
354	EMI	24	MALE	6	OPPO	40000-50000	RED	NO
355	CASH	34	MALE	7	SAMSUNG	30000-35000	RED	NO
356	EMI	28	FEMALE	2	REALME	25000-40000	RED	NO
357	EMI	25	MALE	2	SAMSUNG	15000-25000	RED	NO
358	CASH	21	MALE	7	REALME	50000-75000	RED	NO
359	EMI	21	MALE	5	OPPO	70000-90000	RED	NO
360	CARD	26	MALE	5	REDMI	30000-40000	RED	NO
361	EMI	29	MALE	9	REDMI	15000-20000	RED	NO
362	CARD	34	MALE	5	REDMI	20000-30000	RED	NO
363	CARD	23	FEMALE	9	OPPO	10000-25000	GREY	NO
364	EMI	21	FEMALE	4	VIVO	40000-50000	BLUE	YES
365	CASH	28	MALE	4	OPPO	30000-35000	BLACK	NO
366	EMI	34	MALE	8	OPPO	15000-25000	GREY	NO

FIG: 3.2 Excel data

- Here our product is phone
- So, we are entering all the data of our product like, colour, model, defect etc
- Import the excel data in the Power Bi
- Create the required KPI'S
- Here in our project, we created pie chart, bar chart, forecasting etc.
- We also created Q&A Kpi also
- Now we can easily predict the number of defects and sales by using the kpi's
- We can also identify our product sales using price ranges also
- If we click on the bar chart it shows the percentage count of our product

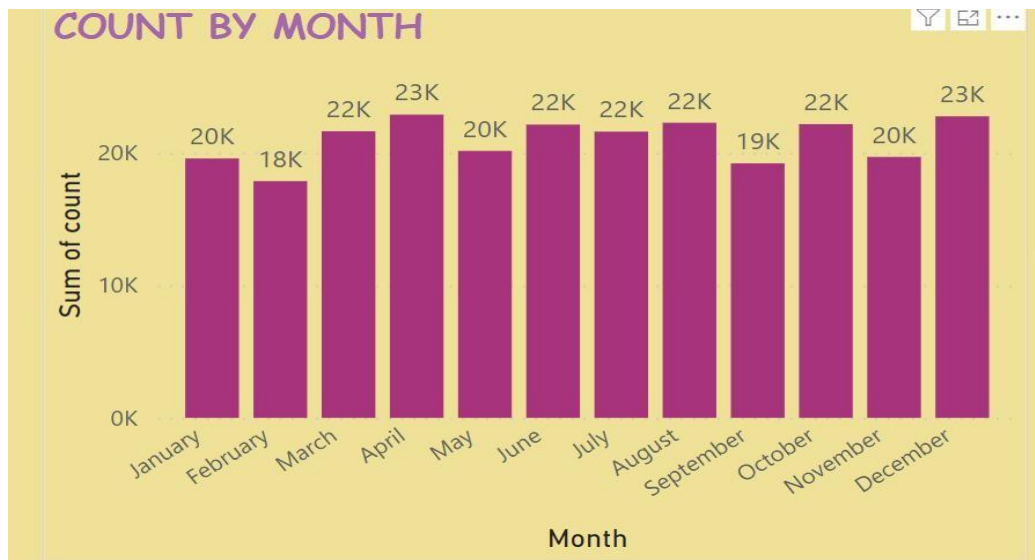


FIG: 3.3 Count by month

Power bi makes our work easier so we can recognize the defect and needs of our customer and we can see more profits

- This bar graph shows month wise count of our product.

Here we can see that in the month of april, december the sales are higher since it's a festive session we will have more offers which will attract customers to buy the product.

- Same way we can see february month is the least number of count.

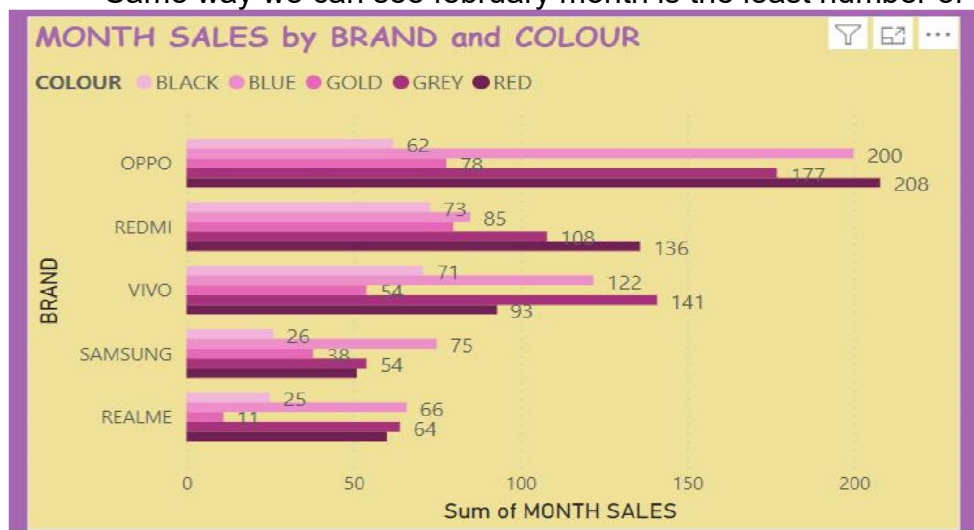


Fig:3.4 Month sales by BRAND and COLOUR

- This chart is based on brand and colour sales
- Oppo brand red colour is purchased more than all other types
- In other ways realme gold is purchased the least compared to other all types

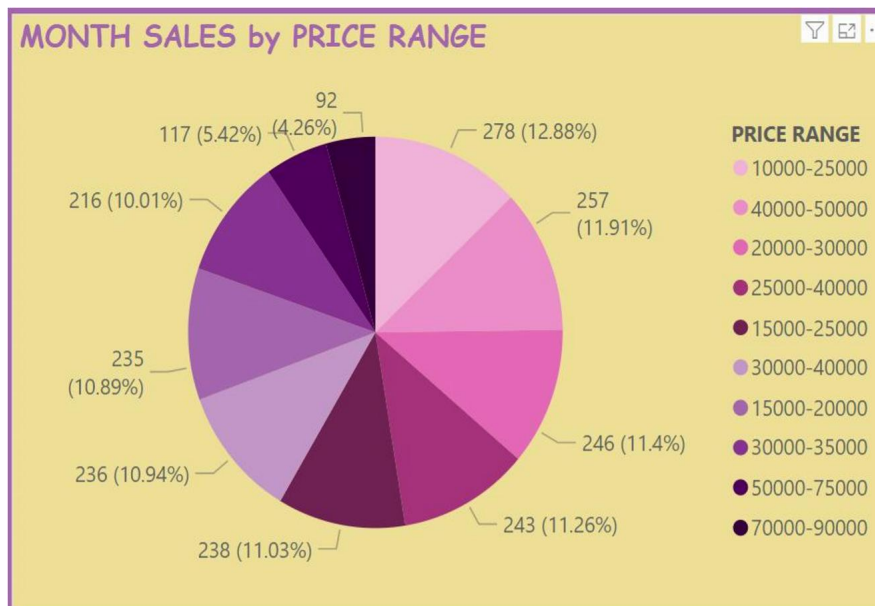


FIG:3.5 Month sales by price range

- This pie chart represents the month sales by price range
- As it seems the price range between 10000-25000 has the highest sales in monthwise sales
- The lowest sales takes place in the price range of 70000-90000 at the average of months
- The price range take a important role in the sales

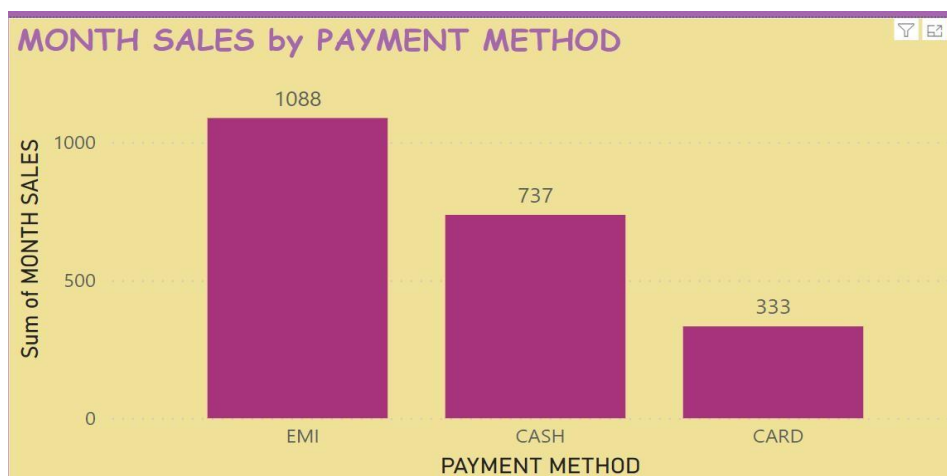


FIG:3.6 Month sales by payment method

- Here it's a simple bar graph
- where x axis represents payment method and y axis represents sum of month sales
- Here the EMI method takes the highest sales as that is the easiest way for people to give amount in installment • Card method has the lowest sales



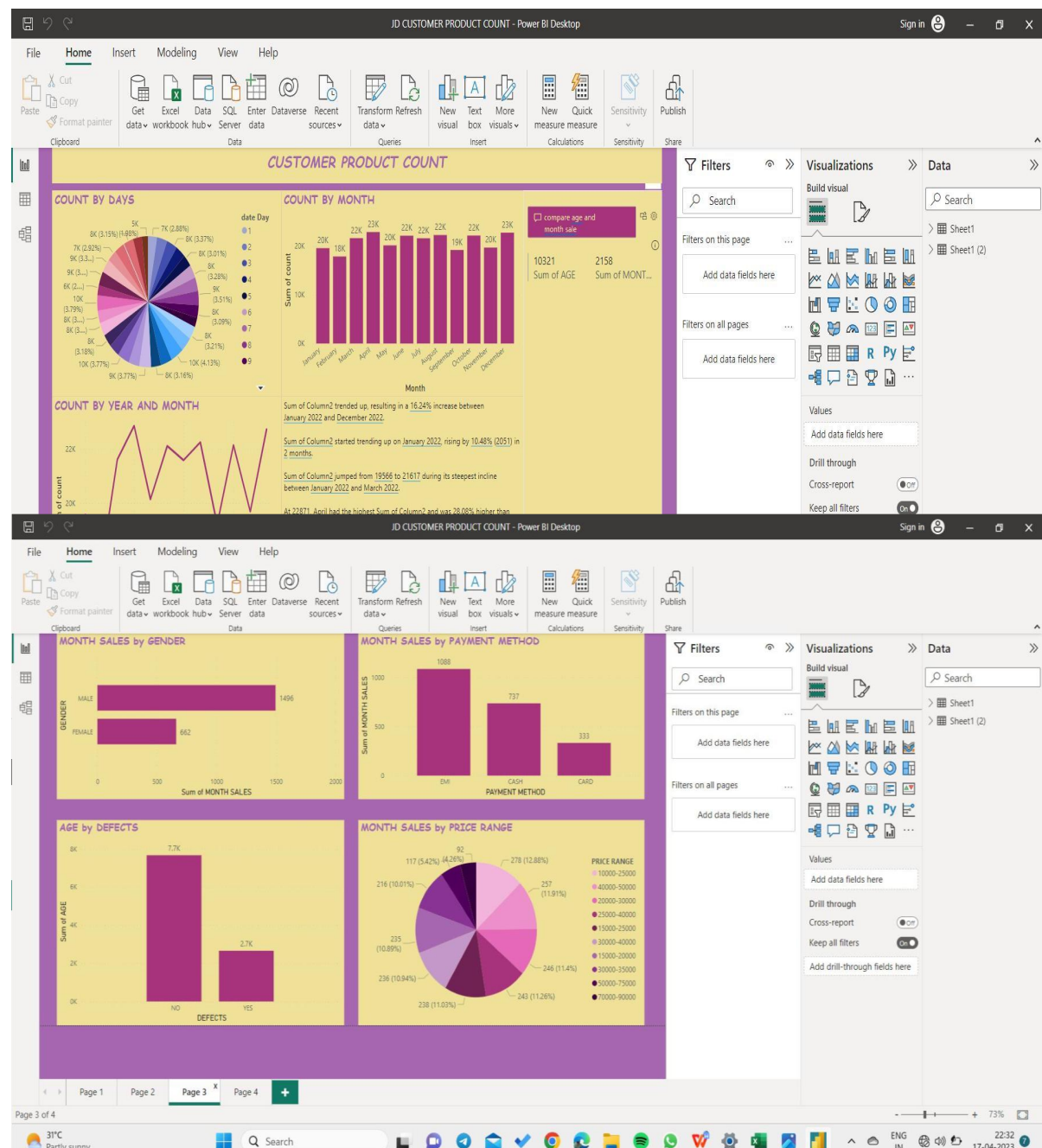
FIG :3.7 Month sales by locations

- This graph shows the sales based on location wise.
- Here x axis is location and y axis are sales
- Here we can see that west locality is highest no. of sales 616
- north is the least number of sales
- South is second highest 522

CHAPTER – 4

RESULT & DISCUSSION

The performance of the Prediction is mostly focused on Prediction accuracy, Accuracy in each table and confusion matrix which shows the number of predictions of each table which can be compared to the instances of each table. From the data visualization it was observed that the april,december month has the highest sales since it's a festive session we will have more offers which will attract customers to buy the product and also west has highest sales among all other areas.



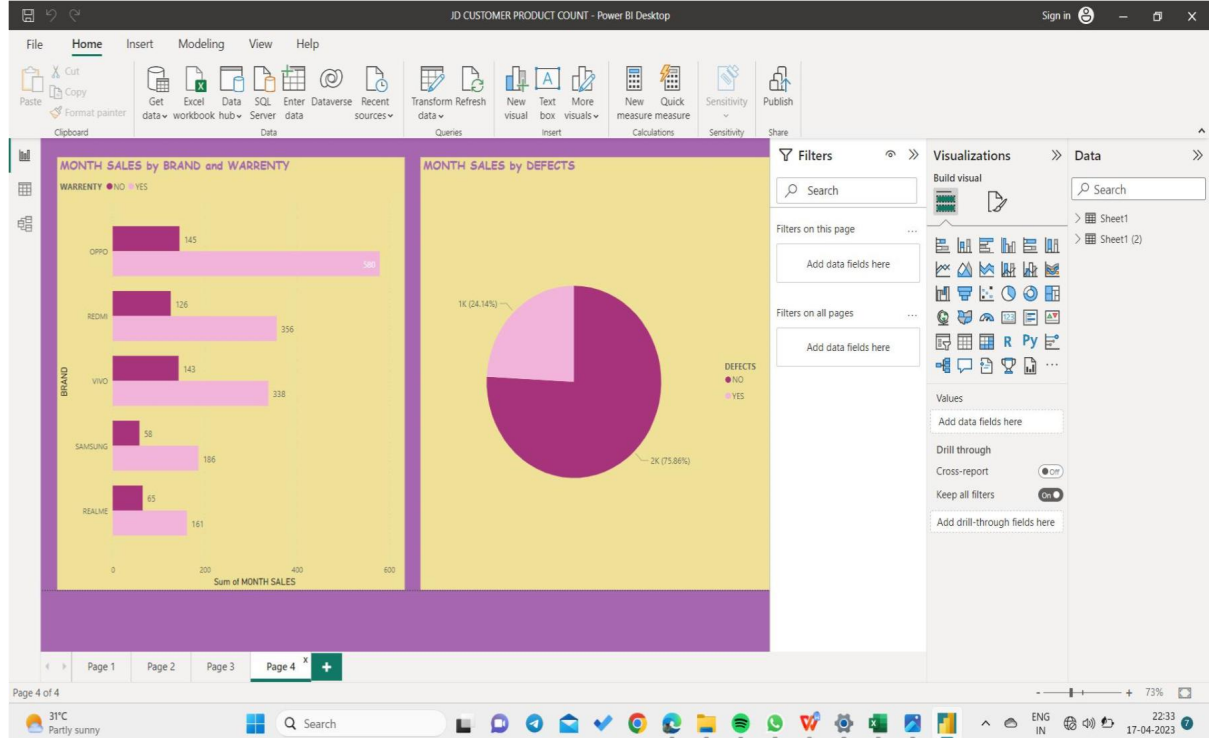


FIG:3.8 Customer product count

> Ultimately, knowing your customers and understanding their behaviour is an activity that you cannot ignore. Carry out a good, thorough study to properly analyse your customers, and you will be able to position your offering in the best possible way that gets them buying.

> Another way of understanding your customer's way of thinking is by controlling their actions. If you have a webpage that only consists of information on your product offering, ensure there are at least two action possibilities. By having two 'calls of action', you are leading your customers to distinct and clearly different outcomes. These different behaviour pathways will inform you what kind of customers you are attracting. There will be the active customers that want instant outcomes and the more thoughtful and guarded individuals.

CHAPTER – 5

CONCUSION & FURTHER WORK

5.1 CONCUSION

Most Stores plan to attract the customers to the store and make profit to the maximum extent by them. Once the customers enter the stores, they are

attracted then definitely they shop more by the special offers and obtain the desired items which are available in the favorable cost and satisfy them. The advantage of forecasting is to know the number of employees should be appointed to meet the production level. Sales drop is bad thing forecasting sales helps to analyze it and it can overcome through the sales drop to remain in the competition forecast plays a vital role.

5.2 FUTURE ENHANCEMENT

For future scope and improvement of this model All the predicted statistical analysis will be help for proper planning and keep storing of all stocks in upcoming years, easily to identify the customer expectation and increase the sales of the products. Data analytics can be used to provide more accurate sales predictions by analyzing historical data and identifying patterns that can be used to forecast future sales. This can help companies to make more informed decisions about inventory management, production planning, and sales forecasting.

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