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Machine Learning Applied in Demand Forecasting and Supply Planning

Metropolia University of Applied Sciences

Master’s Degree

Degree Programme in Business Informatics

Master’s Thesis

12 May 2024

Abstract

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Title:	Machine Learning Applied in Demand Forecasting and Supply Planning
Number of Pages:	99pages + 8appendices
Date:	12 May 2024
Degree:	Master of Business Administration
Degree Programme:	Business Informatics
Instructor:	Antti Hovi, Senior Lecturer

Effective demand forecasting and supply planning are crucial elements in supply chain management. Inaccurate demand information in the supply chain often leads to suboptimal decision-making, resulting in inventory imbalances and customer dissatisfaction. This study aims to address these challenges by leveraging machine learning algorithms and models to enhance demand forecasting accuracy and optimize supply chain operations for the case company.

This study employed an applied action research approach to diagnose the case company's challenges and offer possible solutions. Qualitative methods, including interviews, meetings, and internal document analysis, were primarily utilized for data collection, supplemented by some quantitative data use for model development. Four algorithms: Linear Regression, Decision Tree, Recurrent Neural Network, and Support Vector Machine (Vandeput 2023) were employed to build machine learning models by using data extracted from the company's weekly demand reports. After data processing, feature engineering, training, testing, and validation, Linear Regression emerged as the most appropriate algorithm based on both machine learning metrics and internal evaluation.

The outcome of the thesis is a proposed machine learning-based approach how to reduce excess stock and improve supply shortage that is recommended for integration into the company's existing demand forecasting and supply planning processes to assist decision-making.

Although the existing research discusses machine learning applications in demand forecasting and supply chain management, this study contributes by providing a practical implementation tailored to a real-world company context. Through this study, it aims to pave the way for similar solutions for the case company and wider, in this field.

Keywords	Supply Chain, Demand forecasting, supply planning, Machine learning, Linear Regression, Decision Tree, Recurrent Neural Network, Support Vector Machine.

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1 Introduction

"Forecasting the manufacturer's demand under fluctuation in a random fashion is a challenging task due to a well-known phenomenon Bull-whip Effect." (Lee et al., 1997a. Cited in: Carbonneau et al., 2008).

With the recent rise of machine learning algorithms, it is possible to use new tools to predict more accurately and maintain excellent performance for typical industrial demand. Since 2018, three competitions have been organized specifically on retail demand forecasting, and all of them have been won by machine learning (Vandeput, 2023, Chapter 15.) The benefits of applying machine learning to complex supply chain data are clear: Machine learning will improve forecasting accuracy, leading to cost reduction through decreased inventory and increased customer satisfaction due to improved supply chain deliveries (Agarwal et al., 2021). Moreover, it will improve supply chain visibility, optimise decision making, elevate predictive analysis quality through big data, and enable continuous process enhancement based on real-time insights into system performance. (Carbonneau et al., 2008.)

This thesis aims to explore how the case company can leverage machine learning to enhance demand forecasting accuracy and optimize both demand forecasting and supply planning processes.

1.1 Business Context

This thesis focuses on a case company established in 2000. Based in Finland, the case company is the largest manufacturer of durable IT-devices in the country. The case company has sharply and constantly grown over the last 24 years. (Case Company, n.d. internal document.)

The main products of the case company are used in supermarkets, warehouses, and other industrial occasions. Compared to traditional consumer IT-products, the case company's products are waterproof and drop resistant up to 1.8 m. (Case company, n.d. internal document.) In today's digital world, major companies understand the importance of equipping their employees with larger screens to boost efficiency and get more work done. In the past, small devices such as phones were enough, but now many companies provide their workers with bigger screens, even for outdoor tasks. This provides instant access to company data and facilitates convenient handwritten notetaking. These factors will drive the market growth soon. “The global market size stood at USD 599.1 million in 2017and is projected to reach USD 946.0 million by 2025, exhibiting a CAGR of 5.9% during the forecast period 2018-2025.*” (*Fortune Business Insights, 2023.)

1.2 Business Challenge, Objective and Outcome

The business challenges encountered by the case company are “small fluctuations in demands at the retail level that can cause progressively larger fluctuations in demand at the wholesale, distributor, manufacturer, and raw material supplier levels*.” (*Lee et al., 1997a). This challenge is typical for manufacturing companies but not limited to the case company, because demand-forecasting is a difficult problem that all companies might encounter.

Meanwhile, the case company faces challenge due to its dependence on a key customer which is the market leader in this industry that has strong bargaining power over its whole supply chains. The demand of this key customer changes every week. Simultaneously the key customer requires dynamic changes in the production and delivery plan every week. It results in excess stock and supply shortage in the case company.

The objective of this thesis is *to propose how to utilize Machine learning to reduce excess stock and improve supply shortage*. The Objective can be reached by utilizing Machine Learning to help analyze customers’ demands, make more accurate predictions of demand, and thus help to optimize supplies.

The outcome of this thesis is *a proposal on how to utilize machine learning to assist the case company in reducing excess stock and mitigating supply shortages.*

1.3 Thesis Outline

This thesis will combine exploring literature and best practice in applying Machine learning algorithms in supply chain management. It will also involve the research and development of the case company’s needs. This will be done through interviews with relevant personnel of the case company and data collection from the systems. To achieve this objective, the thesis will use previous current customer order quantity and historical shipment data as a training dataset.

This Thesis comprises seven sections. Section 1 delves into the business challenges faced by the case company, outlines the objectives pursued, and highlights the outcomes achieved throughout this thesis. Section 2 covers the research approach, methodology, data collection, and analysis techniques employed in this study. Section 3 provides an overview of the findings from the current state analysis. Section 4 investigates existing literature and best practices concerning the application of machine learning in demand forecasting. Section 5 presents the initial proposal. Section 6 discusses the outcomes of the testing and validation of the initial proposal. Section 7 finalizes the thesis.

2 Method and Material

This section presents the research methodology, design, and approaches to data collection and analysis employed in this study.

2.1 Research Approach

First, research is categorized into various *research families*: basic vs. applied research, quantitative vs. qualitative, field studies vs. desk studies, etc. Also known as pure research, basic research does not focus on solving practical problems, and may not generate immediate benefits (Sauders et al., 2019, 9). In addition to collecting and analysing data, applied research focuses more on proposing solutions to specific problems by deriving knowledge that has an immediate application (Kananen, 2013, 20). Next, research can be done as field studies and desk studies. Field research collects and analyses data first-hand, and the researcher is doing his or her study in the real world (Sauders et al., 2019, 53). Desk research is done by analysing existing data.

Second, multiple *research methods* are used in this thesis, comprising quantitative, qualitative, and hybrid methodologies. The process of quantitative research includes gathering and analysing data by using statistical methods to test hypotheses (Sauders et al., 2019, 564). Qualitative methodology, in contrast, uses data to explore and understand phenomena, such as interviews, observations, and case study i.e. via non-numerical methods. Interviews make an example of a qualitative research method. Hybrid methodology employs both quantitative and qualitative research methodologies to attain a more thorough comprehension of a research topic (Sauders et al., 2019, 181.)

Third, research methodology also includes a selection of *a research strategy* (Sauders et al., 2019, 57). Research strategies rely on the character of the issue, the corresponding context, and the data needed to develop effective solutions. Some common research strategies used within corporate sector include Surveys, Case studies, and Action research. Surveys are used to collect and organize data from specific groups of people through various means (such as telephone, email, online questionnaires), and then draw conclusions on this basis and help gather data on customer preferences, market trends, and understand individuals' views, attitudes, and behaviors in a variety of areas (Yin, 2003, 9). Case studies, acknowledged across various domains such as business, law, policy, and health services, offer valuable insights. Case studies can illuminate best practices and potential solutions from similar businesses or industries. (Yin, 2003, 13-14.)

According to Coghlan & Brannick (2014), Action research focuses on solving practical problems through collaborative and iterative approaches (Coghlan& Brannick, 2014, 5). Figure1 below analyzes the outcomes, intended and unintended, of actions in a constructive process, focusing on the alignment of the initial plan, the appropriateness of actions, and their impact on the continuous cycle of planning and constructing (Coghlan& Brannick, 2014, 11.)

Figure 1. Spiral of Action research cycles (Coghlan & Brannick 2001).

Recently, there has also emerged a popular research strategy for thesis research called Applied action research. “It involves actively engaging in organizational development to enhance operational processes.” (Kananen, 2013, 21). Although both Action research and Applied action research share similar methodology, applied action research is more specially focused on practical problem-solving in real world setting. Applied action research makes difference with Action research as it has fewer iterations, and it is concerned with the practical result with improvement for the best. (Kananen, 2013, 13-22.)

This study employs applied action research to identify the specific issues of the company and propose solutions. Three main methods of data collection are used in this thesis, interviews, meetings, internal document analysis and data from the systems. Therefore, it belongs to the qualitative methods type of study. Qualitative research methods used in this thesis include interviews, meetings, discussions, observations, and the quantitative methods are used to analyze the case company's internal data. Data collection & analysis in this study are used in three iterations: in CSA, to gain a more comprehensive understanding of the case company's current state and map out its current processes; second, for the proposal building, and third, for validation. Data will also contribute to developing the *machine learning algorithms and models* during proposal development.

2.2 Research Design

Figure 2 below shows the research design of this study.

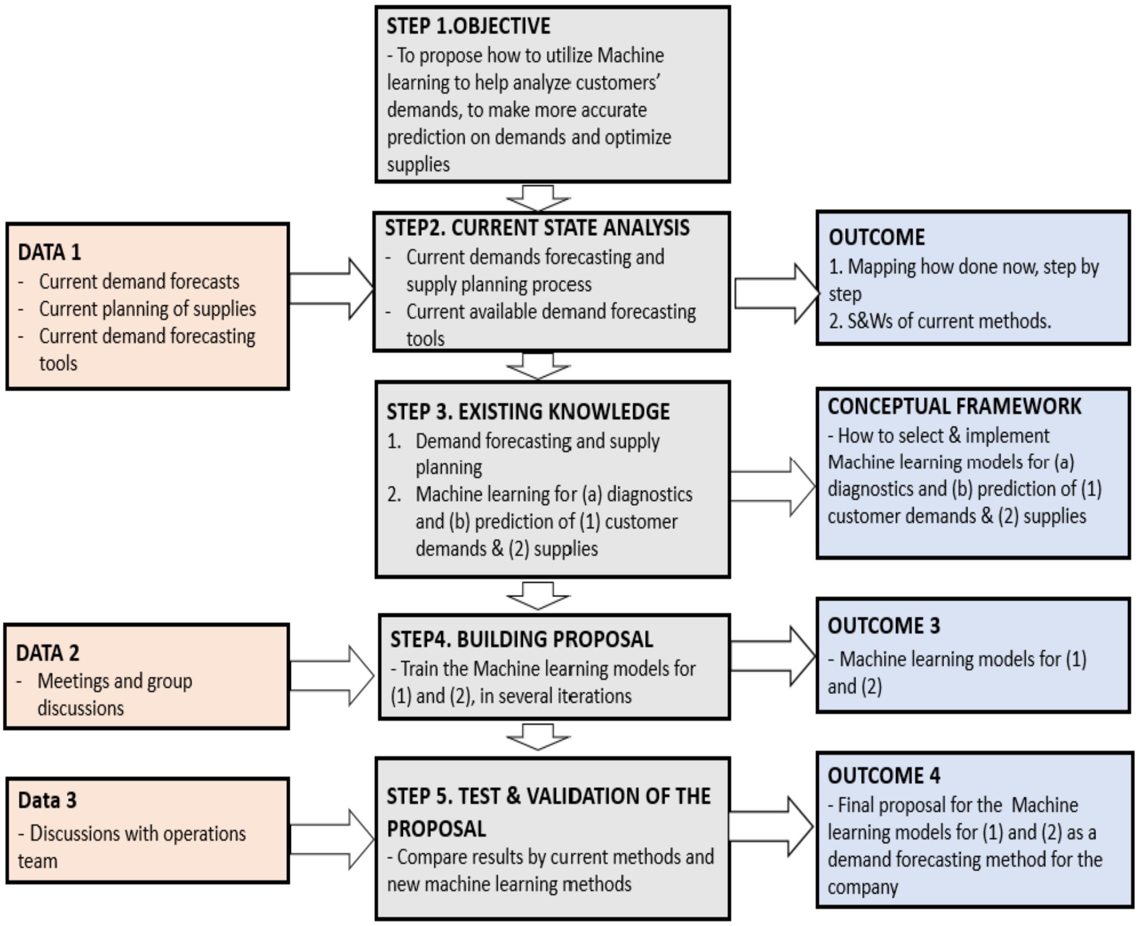


Figure 2. Research design of this study.

As shown in Figure 2, this study is conducted for seeking more accurate demand forecasting approach in the case company. It starts with this goal and then proceeds to examine the current processes of customers' demand forecasting and suppliers' supply planning. The goal of CSA is to map out and standardize the current process and discover strengths and weaknesses of the demand forecasting and supply planning in the case company. Then, the CSA also analyses the existing tools and processes involved in demand forecasting and supply planning.

Next, the thesis delves into the existing knowledge and best practice for developing a machine learning model for demand forecasting and supply planning. The outcome of this step is to select and implement a machine learning model for diagnostics and prediction of demands and supplies.

The next step is to make a proposal. The outcome of this step is to propose machine learning models for demand forecasting and supply planning. Finally, in the validation phase, it proposes the most appropriate machine learning model for demand forecasting to the case company by comparing its results with the current demand forecasting outcomes.

2.3 Data Collection and Analysis

This study gathers information from diverse datasets. The study uses qualitative data, but also some quantitative data sources. The data collection details are demonstrated as follows.

Table 1. Data collection for this thesis.

	Participates/role	Data Type	Description	Date, Duration	Documented as
	Data1, Current State Analysis				
1	Key customer	Online Interview	Current Gap between demand and supply	November 2022 60 minutes	Meeting Minutes
2	Operation Manager	Online Interview	1.Demand and supply 2.Current demand forcasting process 3. Drawbacks of current process	October 2022 60minutes	Meeting Minutes
3	Order Fulfillment Manager	Online Interview	Demand forecasting method	December 2022 60minutes	Meeting Minutes
4	Sourcing Manager	Online Interview	Current Inventory and shortage review	December 2022 60minute	Meeting Minutes
5	Data Scientist	Online Interview	Machine learning algorithms discussion based on the current data collection	December 2023 60minutes	Meeting Minutes
	Data2, Proposal building				
6	Operation Manager, Order Fulfillment Manager, Sourcing Manager	Brainstorming	List all factors that could affect the demands and supplies	January 2024 60minutes	Meeting Minutes
7	Data Scientist	Brainstorming	Brainstorm on proposing forecasting algorithm and model	February 2024 60minutes	Meeting Minutes
8	Data Scientist	Online meeting	ML model Discussion	March2024 60minutes	Meeting Minutes
	Data 3, Validation				
9	Data Scientist	Online meeting	ML Results Review and Evaluations	March 2024 60minutes	Meeting Minutes
10	Operation Manager, Order Fulfillment Manager, Sourcing Manager	Group Interview/ Final presentation	Validation and evaluation of a new forecasting by using machine learning model. ML process integrated to demand and supply planning process.	March 2024 60minutes	Meeting Minutes

As illustrated in Table 1, qualitative data was acquired in three phases for this thesis. The initial phase was dedicated to gathering Data 1 and focused on conducting a thorough analysis of the present state. It included the current gap between the demand and supply, and the current demand and supply process. The data was collected through online interviews with the main stakeholders such as Key Customers, Operation Manager, Order Fulfilment Manager, Sourcing Manager, and Data Scientist. As a result, variables that will influence the ML algorithm and model construction were identified.

During the second phase, Data 2 was to gather input from the case company regarding the enhancement of the proposal. It listed all factors that could affect the demand and supply in terms of brainstorming on proposing forecasting algorithms and models. Furthermore, the data also included stakeholder feedback for process optimization.

In the third phase, Data 3 was gathered during the validation process of the initial proposal. It included feedback for the proposal from the case company.

Moreover, Table 2 displays the quantitative data sources utilized in this study, comprising customer order quantity and shipment quantity.

Table 2. Data collection for Machine Learn Model Build.

	Data Type	Description	Date	Documented as
1	Customer's weekly Demand and supply report	Machine learning training data	01/03/2024	Excel document
2	Factory's weekly shipment report	Machine learning training data	01/03/2024	Excel document

The above Table 2 presents a few internal data from the case company. It included the Customer’s weekly demand and supply report and factory’s weekly demand and supply report. The data is extracted from the report, cleaned, and transformed into a CSV file. Afterward, it goes through data processing and feature engineering before being utilized for building machine learning algorithms and models. A comprehensive description of the dataset is provided in Section 5. Section 3 below will explore the key findings of current state analysis.

3 Current State Analysis of Demand Forecasting in the Case Company

This section presents the findings of the Current State Analysis (CSA). It begins with an overview of the current demand forecasting and supply planning process analysis. This is followed by an examination of the demand forecasting methods currently employed by the case company. Finally, it highlights both the advantages and drawbacks of the present situation analysis regarding demand forecasting and supply planning in the company.

3.1 Overview of the Current State Analysis

The goal of the current state analysis was to review the existing demand forecasting, supply planning processes, and identify its strengths and weaknesses in the case company. The analysis was conducted through meetings, and interviews with key stakeholders, supplemented by the analysis of internal documents.

First, the emphasis was placed on the current demand and forecasting process, and demand forecasting methods. It starts from Interviews with key stakeholders, including the operation manager, order fulfilment managers, and sourcing managers. Afterward, the initial process of current demand forecasting and supply planning was mapped out.

Secondly, the analysis focused on the supply planning analysis. It was conducted through interviews with the relevant stakeholders. Therefore, the current demand forecasting method was outlined.

Finally, the case company's current state analysis highlighted and summarized the pros and cons of the existing demand forecasting process and methodology in the key findings.

3.2 Current Demand Forecasting and Suppling Planning Process

This section analyzes the current demand forecasting process in the case company. First, it describes the process map of demand forecasting and supply planning process and responsibilities of main stakeholders. Second, it describes demand forecasting tools used in the case company’s supply chain. Third, it analyzes the process and identifies the key findings from it. Finally, it points to the strengths and weaknesses of current state analysis, as well as selected focus areas for development.

3.2.1 Process map of Demand Forecasting and Supply Planning

Based on interviews with internal stakeholders and thorough analysis of the case company's internal documents and workflows, a demand forecasting and supply planning process map were developed, as presented in Figure 3.

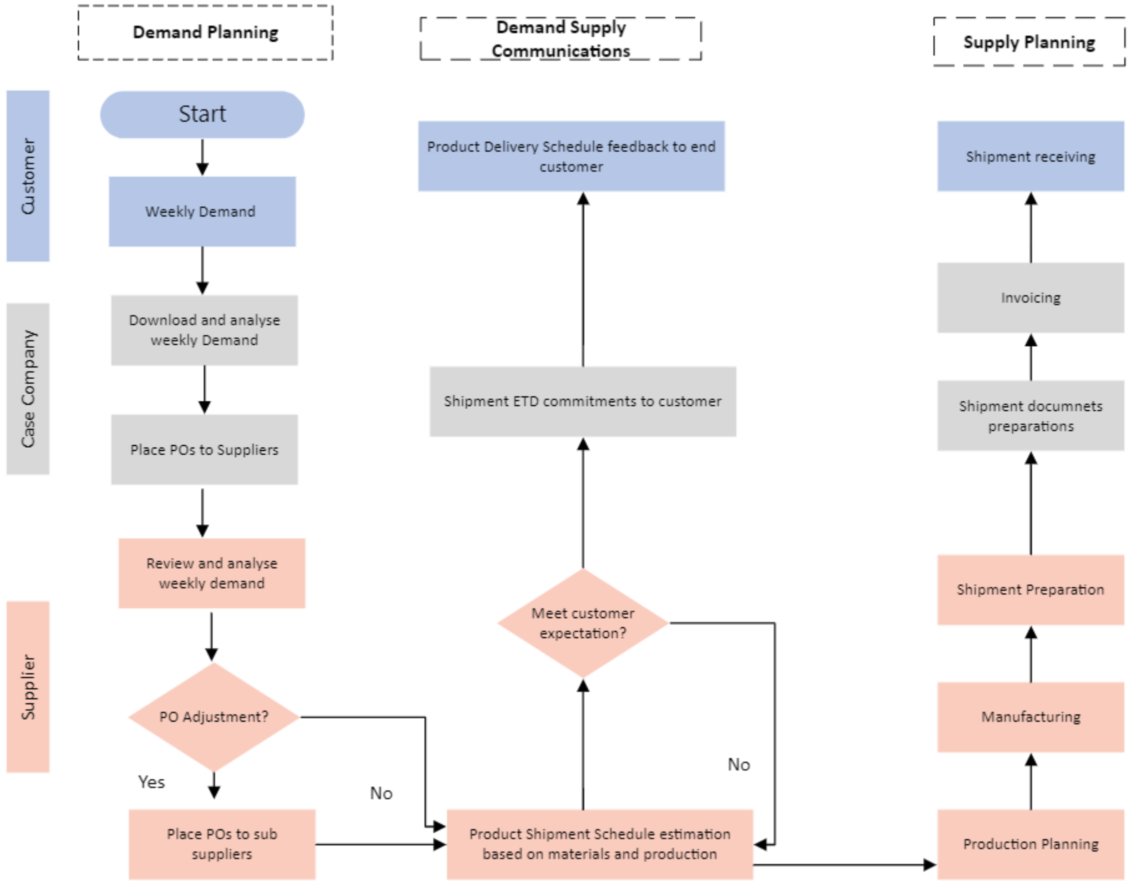


Figure 3. Current Demand and Supply Planning process in the case company.

Figure 3 shows the involvement of three key stakeholders in the demand forecasting and supply planning process: customers, the case company, and suppliers. The case company utilizes an information sharing platform to access the forecast data. After retrieving and analyzing the latest weekly demand, the case company forwards the forecasting data to its suppliers and places purchase orders (POs). The suppliers review their material status, provide delivery plans, and place material POs with their suppliers. After receiving the delivery plan, the case company commits to it via the information sharing platform, ensuring customer satisfaction. The customer acknowledges this commitment and reports to its own customers. Upon the product completion, the supplier ships the products to the customer, while simultaneously, the case company generates invoices. Ultimately, the customer settles the payment, concluding the transaction.

However, the customer's demand on the sharing platform fluctuates weekly, necessitating the case company to adjust delivery commitments accordingly. With the customer having significant bargaining power in the supply chain, the company must update delivery plans based on the latest demand trends. Notably, if demand is withdrawn from the platform, products cannot be shipped out, hindering invoicing. Therefore, both the case company and its subcontractors bear the risks and responsibilities associated with fluctuating demand.

3.2.2 Roles and responsibilities

The customer's global supply planning team updates the demand forecast in their demand forecasting system. In the case company, the order fulfillment manager downloads the weekly forecast from the customer's system and sends it to Tier 1 suppliers.

The operations manager is responsible for updating production plans and allocating production capacity. The sourcing manager reviews the materials status and prepares Critical to Build (CTB) reports in collaboration with the Tier 1 suppliers. The case company works with three Tier 1 suppliers who manufacture products on their behalf. These Tier 1 suppliers are responsible for purchasing components from their own sub-suppliers and managing their supply chains respectively.

3.2.3 Current available tools

The E2open platform is used between the case company and its customer to share latest demand forecast, supply commitments as well as shipments and invoicing. Currently, the case company also relies on E2open system as a demand forecasting tool. Moreover, the Wise Time ERP system is used as a supply planning tool where the case company places purchase orders to its tier one suppliers.

3.2.3.1 Supply chain information sharing platform: E2open.

> *“Information sharing is a vital aspect of coordination amongst parties in a supply chain. Information sharing can increase supply chain efficiency by reducing inventories and smoothing production.”* (Raweewan, M., & Ferrell, W. G, 2018).

Many studies have found that information sharing and forecasting methods significantly influence the performance of the supply chain, particularly in mitigating the *Bullwhip effect*. (Wright &Yuan, 2008). However, it is widely believed that “advanced information technology can change modern business practice and make the collaborative SCM possible.” (Kumar & Pugazhendhi, 2012.) This topic is further discussed in Section 4.

The case company relies on the E2open supply chain platform to facilitate seamless communication with its customers regarding forecast updates, supply commitments, and shipment tracking. E2open stands as a leading Software-as-a-Service (SaaS) solution in the realm of supply chain management, serving diverse industries worldwide, including Aerospace and Defense, Automotive, Food and Beverages, High Tech, and Chemical Industries. Renowned companies such as Michelin, Schneider Electric, and Nvidia are among the many leveraging the capabilities of the E2open platform. (E2open, 2024.)

The utilization of the E2open platform offers several distinct advantages. The key advantage among them is its ability to unify stakeholders across the supply chain ecosystem, seamlessly connecting customers, retailers, distributors, and suppliers within a single digital interface. This consolidation streamlines communication channels, fostering enhanced collaboration and efficiency throughout the supply chain network. (E2open, 2024.) Retailers and distributors benefit from the platform's user-friendly interface, allowing them to input sales forecasts directly into the system with ease. This direct integration ensures that forecast data is readily accessible to suppliers in near real-time, empowering them to make informed decisions and optimize their production and inventory management processes accordingly. (E2open, 2024.)

Furthermore, upon the completion of supply commitments by the order fulfillment manager in the case company, the end customer gains immediate visibility into the estimated delivery date. This transparency eliminates any information gaps that may exist between suppliers and end customers, fostering trust and reliability within the supply chain. (E2open, 2024.) The E2open platform enhances collaboration and efficiency within the case company's supply chain operations. By seamlessly connecting stakeholders and providing real-time visibility into critical supply chain metrics, E2open empowers companies to navigate the complexities of modern supply chain management with confidence and agility. (E2open, 2024.)

Figure 4 below shows the overview of E2Open system, where it connects all the party involved in the supply chain to one platform.

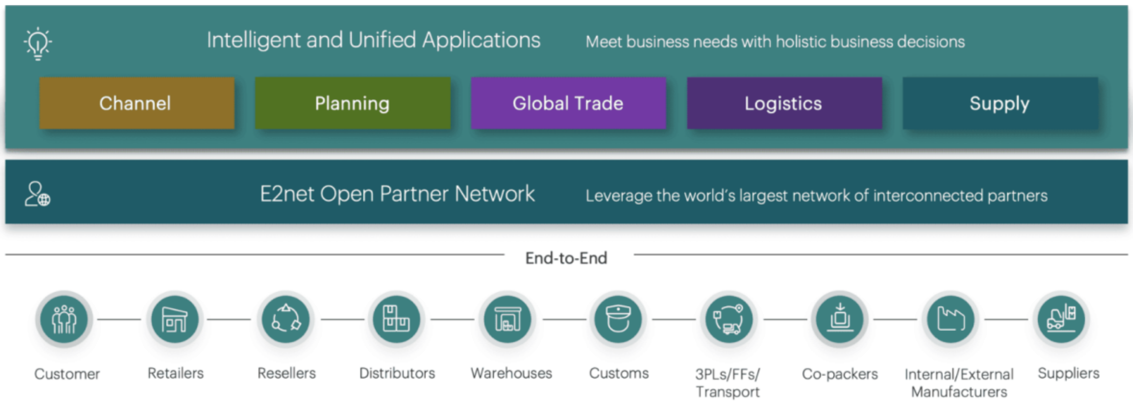


Figure 4. The connected supply chain platform from E2open (e2open).

As shown in Figure 4, E2open connects customers, retailers, resellers, distributors, warehouses, customs, transporters, copackers, internal/external manufacturers and suppliers into one platform, product information starting from forecasting to supply, and shipments are stored in the same platform and shared within all the parties involved.

3.2.3.2 Demand forecasting methods

The case company fully replies on the forecast data from E2Open platform, which was updated by end customers and reviewed by the global supply planning team. Figure 5 below shows the main E2open user interfaces, which includes Supply Planning, Supplier Visibility, PSM, Upload/Download supplier commitments, and E2open Analytics sub functions.

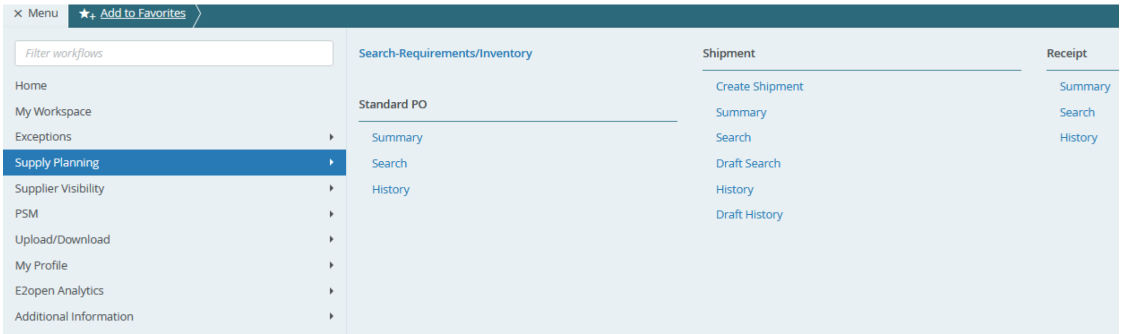


Figure 5. E2Open User interface (e2open).

As shown in Figure 5, Demand Forecast can be found by clicking "Search-Requirements/Inventory" under supply planning category. All purchase orders can be found under standard PO, shipments can be created and followed up under shipments category.

Figure 6 below shows demand and supply status for one sample product G21E-00A6.

Supply Consumption	01/08/24	01/15/24	01/16/24	01/17/24	01/18/24	01/19/24	01/20/24	01/21/24	01/22/24	Total
	Default - 2024-01-08 -- 2025-01-19 All bucket dates are in system time.									
G21E-00A6 2 // --										
Net Booked Orders							604	0	0	1,102
Gross Forecast										0
On Hand (Weekly)		121								121
On Hand (Daily)							67			67
Net Requirements						603				1,352
Gross Booked Orders (Daily)		470		1	200					1,169
RMA Stock Rotation										0
Internal Requisition										0
WIP										0
Safety Stock										0
On Hand SOI (Daily)										0
Cumm Gross Booked Order +/-	0	0	0	0	0	0	-604	-604	-604	

Figure 6. Demand and supply for one example product in E2Open (e2open).

As shown in Figure 6, from demand point of view, it has 470pcs Gross booked order on 01/20, 1pcs Gross booked order on 01/17, 200pcs Gross booked order on 01/18, Gross forecast for this product is 0, since it has on hand quantity 67pcs, it ends up net booked order quantity is 604pcs. Hence the company needs to deliver 604pcs of products before 01/20 to meet the customer demand on time.

Table 3 below presents a summary of forecast data for select products in the E2open system for February and March 2024.

Table 3. Example of product forecast in E2pen system (e2open).

		Feb		Mar	
Part Number	Site	Net booked orders	Net Requirements	Net booked orders	Net Requirements
0801AB06	USA	765	0	765	1
300035	EU	28	0	28	25
350022.1	SG	0	0	0	9
3337	EU	0	0	0	1

As shown in Table 3, the "Net Booked Orders" column indicates the quantity of customer orders received, while the "Net Requirements" column represents the forecasted quantity of customer orders. Net-Booked orders are confirmed orders from customers. It may increase over time. However Net Requirements may fluctuate. The company will aggregate Net-Booked orders and Net Requirements to generate total purchase orders for suppliers.

In summary, the company relies on the forecasting data from E2open system, they are not using any other forecasting tools to modify or optimize this forecasting data. One challenge arises from the unpredictable ordering behavior of end customers, who may place purchase orders for varying quantities at any time. Importantly, due to the excessive cost of products, implementing safety stock for all items is impractical.

3.2.3.3 Supply planning methods

Order fulfillment specialists place POs to their suppliers on a weekly basis. To understand how the case company makes supply planning, three interviews were carried out with three order fulfillment specialists in the case company. Table 4 illustrates the responses of order fulfillment experts regarding strategies for demand forecasting and order placement with Tier one suppliers.

Table 4. Internal interviews, responses.

Question: How do you know what quantity to be ordered for next week, next month, and next 2 months?		
Answer 1	Answer 2	Answer 3
I fully reply on E2open system. If E2open system shows forecast of 100pcs, I will order 100pcs. (Order fulfillment specialist A)	I analyze both our shipment history and the forecast data in E2open. If we've consistently shipped large quantities in the past but the future forecast is significantly lower, I may increase the order quantity. Conversely, if our historical shipment quantities are small but the future forecast indicates higher demand, I might decrease the ordering quantity. (Order fulfillment specialist B)	The forecast data in the E2open system fluctuates weekly. It's impractical to adjust our purchase orders with our suppliers every week. Instead, I maintain stability by averaging the forecast data for the next four weeks and keeping the purchase order quantities unchanged for that period. (Order fulfillment specialist C)

Table 4 interview results display that the company level Demand forecasting and supply planning tool *does not exist*. The purchase order quantity and supply planning solely rely on the e2 open data and order fulfillment specialists' own experience.

Based on the above analysis of the current demand forecasting process in the case company, it can be concluded that the company benefits from a robust information-sharing platform provided by its customers. This platform facilitates the extraction of various data, including demand, inventory, shipments, and orders. However, a notable gap exists in the absence of a company-level demand forecasting tool. This results in a heavy reliance on individual expertise for forecasting and procurement decisions. It highlights the need for the implementation of a company-level demand forecasting solution to enhance forecasting precision.

3.3 Analysis & Key Findings from the Current Demand and Supply Planning Process

To understand the consequences of the missing company-level demand forecasting methods, cross functional meetings and interviews were conducted with several key stakeholders in the case company.

Firstly, the stakeholders agreed that the customer forecasts fluctuate frequently. The supply chain manager must adjust purchase order quantities very often, as described by one of the supply Chain managers below:

> *“Customer demand and forecasts change every week. We must adjust our orders to our factory and manufacturing partners accordingly. In some special occasions, customers even alter their demand for the following week.” (Supply Chain Manager.)*

Secondly, inaccurate and fluctuating demand have caused excess of finished products, as explained by the case company´s Operations Manager during the interview:

> *“Due to customer demand change, some of the products that we produced were not be able to ship to customer. The products became excess finished products stock. On the other hand, customers were chasing urgent production and delivery of products that orders were recently placed.” (Operations Manager.)*

Finally, sourcing managers can order wrong components due to the constantly changing demand. One of such comments is shown below:

> *“Our orders to our suppliers change too often, some of the components and materials just arrived at our factory become excess materials. We need to understand better what products our customers really want, and we should order right products from our suppliers.” (Sourcing manager.)*

Table 5 below summarizes the interview results and points to the main problem areas, reported by each department in the case company.

Table 5. Identified problems and responsible units (based on the interview results).

Problem	Description of the problem	Responsible
1	Customers update demand on weekly basis, Component lead time is at least 4weeks.Componnets prepared 4 weeks ago might not right for products to be produced and shipped after 4 weeks.	Customer, Order Fulfilment
2	Weekly changing demand causes excess materials stocks, and new components shortage.	Sourcing, Finance
3	Materials Shortage causes low-capacity usage in production, shipments are delayed.	Operations, Order Fulfilment
4	The customer is not satisfied with the overall performance of the case company.	The Case company, and the Customer

As shown in Table 5, incorrect materials and components were ordered, due to the customer demand changes and fluctuations. This caused excess materials and components stock. In addition, there is not enough lead time to order the correct components and materials, therefore, it causes low-capacity use in production. Customer shipments are often delayed. Most importantly, customers are not happy with the operation performance of the case company.

3.4 Summary of the Current State Analysis Results

This section presents the strengths and weaknesses of the current Demand Forecasting and Supply Planning in the case company. Finally, it indicates the selected focus area of this thesis.

3.4.1 Strengths and Weaknesses of the current Demand Forecasting and Supply Planning practices

The above analysis ends with identifying strengths and weaknesses of the current demand forecasting and supply planning practices at the case company. The analyzed results are summarized in Figure7 where strengths are highlighted in blue, and weaknesses are highlighted in pink.

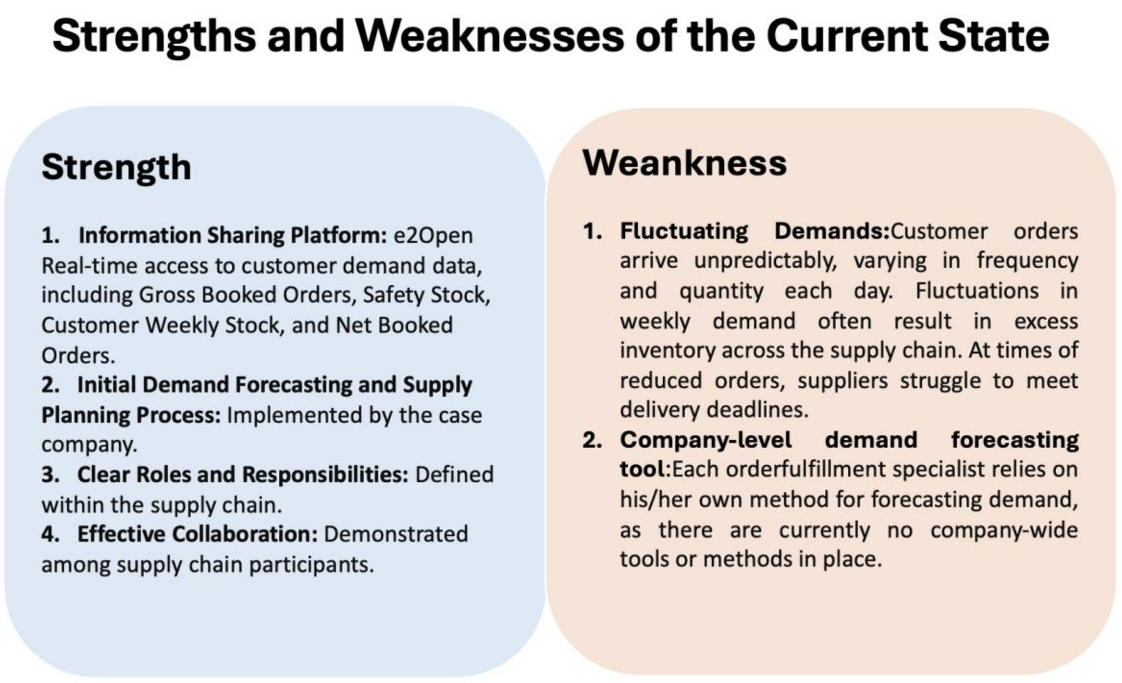


Figure 7. Summary of strengths and weaknesses of the current state.

As seen in Figure7, the demand forecasting and supply planning processes shows both strengths and weaknesses. These strengths comprise four key elements. Firstly, the implementation of an Information Sharing Platform enables real-time access to demand data, including Gross Book-Orders, Safety Stock, Customer Weekly Stock, and Net Booked Orders. Secondly, the case company has established an initial demand forecasting and supply planning process. Thirdly, clear roles and responsibilities are presented within the case company. Lastly, effective collaboration among supply chain participants has been demonstrated.

The weaknesses are divided into two components, as illustrated below. Firstly, fluctuations in the case company's weekly demand frequently led to excess inventory and supply shortages. Secondly, the case company lacks a company-level forecasting method, resulting in demand forecasting relying solely on individual experience rather than expertise.

3.4.2 Selected Focus Areas

The analysis of strengths and weakness highlights the importance for developing demand forecasting and supply planning tools in the case company. It is crucial to implement advanced demand forecasting methodologies at the organizational level.

Additionally, the identified weaknesses inform the search for knowledge and best practice in the next phase. In the next phase, this thesis will focus on three key areas: demand forecasting, machine learning, and machine learning applied in demand forecasting and supply planning.

First, under demand forecasting, the phase explores three main aspects:

1. Introduction to the demand forecasting.
2. Demand distortion and amplification-Bullwhip effects.
3. Demand forecasting method: Machine learning.

Second, under machine learning, the phase divided into six essential components:

1. Machine learning definition.
2. Machine learning development.
3. Machine learning categories
4. Machine learning algorithms.
5. Data preparation.
6. Modeling, modeling evaluation and optimization.

Third, under the machine learning applied in demand forecasting and supply planning the aim is to establish a connection between the ML system and demand forecasting and supply planning.

Next, the chosen focus areas will explore to find the relevant existing knowledge and best practice, and thus to prepare for the proposal building in Section 5.

4 Existing Knowledge and Best Practice of Machine Learning Applied in Demand Forecasting and Supply Planning

This section presents the existing knowledge and best practice of ML applied in demand forecasting and supply planning, commonly referred to as the literature review. Firstly, it starts with an introduction to demand forecasting, covering its definition, importance, and a famous phenomenon *Bullwhip effect*. Secondly, it explores machine learning. Thirdly, it introduces the application of machine learning in demand forecasting and supply planning. Finally, it concludes and sets the stage for the final proposal.

4.1 Demand Forecasting

> "*Demand forecasting is a crucial component of demand management, directly impacting manufacturing companies' planning, and revenues through the supply chain*" (Rožanec et al., 2021).

It aims to achieve a comprehensive understanding of customers' preferences, determining the products they desire, the quantity of products they require, and the timing of their demand (Vandeput, 2023, Chapter 2). In supply chains, many decisions, such as determining procurement quantities, production volumes, shipment schedules, and inventory levels are based on demand forecasts. The more accurately future behaviours and needs of clients are captured, the more informed decisions can be made. This leads to improved service levels, enhanced production and supply planning, reduced waste, and lower overall costs. (Vandeput, 2023, Chapter 3).

Demand is influenced by numerous uncertain factors such as seasonality, promotional effects, emerging trends, unexpected crises, and the commercial behaviour of competitors in the market, etc. (Borucka, 2023). These factors present significant challenges in making accurate forecasts. Many research papers have analyzed the distortion and fluctuation present in demand. One significant uncertainty is the amplification of orders, termed the *Bullwhip effect*, which was first "analyzed by Forrester (1961) and demonstrated through the famous beer game by Sterman (1989)." (Dutt et al., 2018.)

4.1.1 Demand distortion and amplification-Bullwhip effect

The Bullwhip Effect is a well-known phenomenon within supply chain management. Initially identified by Forrester in 1958, it highlights the amplification of fluctuations in demand along the supply chain. MIT's creation of the Beer Game further presented this concept, aiding both academic and industry comprehension. In 1989, Sterman provided a more concrete understanding and emphasized how decision-makers can stumble due to complexities such as "*multiple feedback loops, time delays, and nonlinearities*." The *Bullwhip Effect* remains a fundamental aspect of business operations. (Lee et al., 2004.)

In 1990, Lee and his colleagues conducted interviews with P&G executives. They observed the company was struggling with the *Bullwhip effect*. Their research revealed that similar issues were encountered by other companies such as *HP, Canon, 3 Com*, and *Intel.* This indicates that this phenomenon is pervasive across industries (Lee et al., 2004).

According to Lee et al., (1997a), the *Bullwhip effect* is a universal phenomenon in supply chains. This phenomenon is characterized by the amplification and distortion of demand information.

> *"Distorted information from one end of a supply chain to the other can lead to tremendous inefficiencies: excessive inventory investment, poor customer service, lost revenues, misguided capacity plans, ineffective transportation, and missed production schedules." (Lee et al., 1997a.)*

Demand fluctuations can occur even with slight variations. Since each player in the supply chain makes decisions based on forecasts and inventory control speculations, these interactions without accurate forecasting can lead to amplified orders. "As we move up the supply chain, we observe larger swings in orders compared to the fluctuations in the markets." (Lee et., 1997a.) To aid understanding, the Bullwhip effect is illustrated in Figure 8 below.

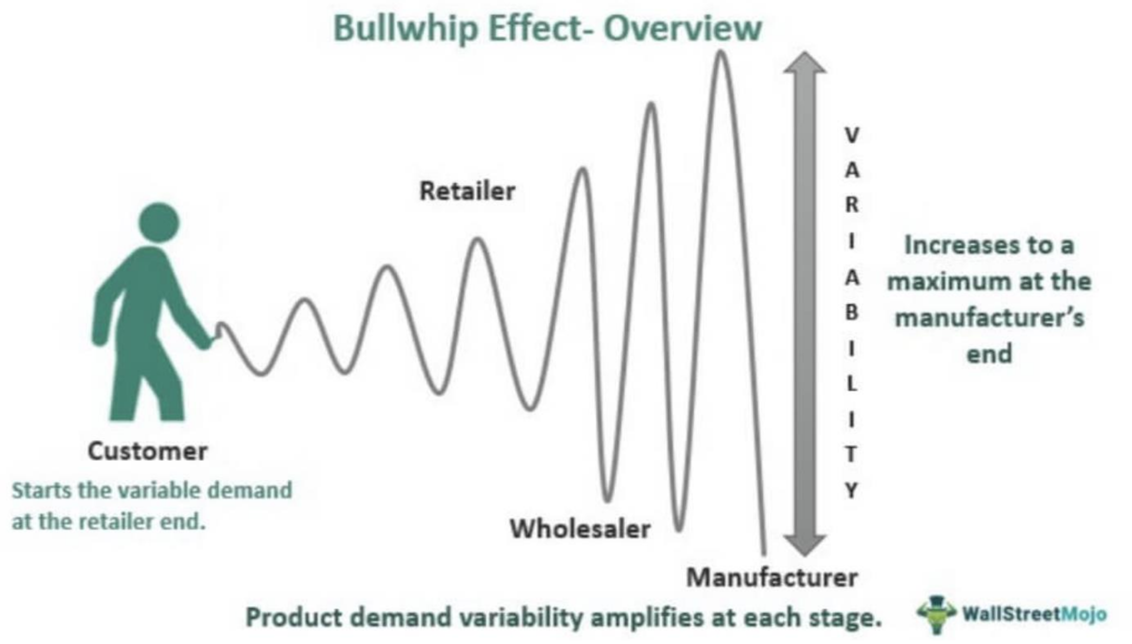


Figure 8. Bullwhip effect (WallStreetMojo, 2024).

As seen in Figure 8, there is a graphical representation of the *Bullwhip effect*. When the whip is cracked, the handle moves only 60 degrees, while the tip of the whip moves more than 360 degrees. This analogy vividly captures the dynamics of the market: small shifts in demand, starting from customers and moving through retailers, wholesalers, and manufacturers, can amplify along the supply chain, causing substantial fluctuations. These fluctuations pose challenges for production planning, inventory management, capacity planning, and transportation logistics for upstream suppliers. (Lee,1997a.)

The bullwhip effect occurs when retailers inaccurately predict demand. It may lead to a widening gap between supply and demand. For instance, if a retailer typically sells 30 packs of toilet paper every day, but he experiences a sudden spike of selling 80 packs of toilet paper one day. He may overestimate future demand and order 100 packs to meet this perceived increase. Afterward, the distributor might order double the quantity, or more quantity from the manufacturer to avoid stockouts. Therefore, the manufacturer might produce 300 packs of toilet paper. Consequently, the initial demand surge of 80 packs of toilet paper at the customer level escalates to 300 packs of toilet paper at the manufacturer's level. Retailers often make forecasts based on current trends which might lead to excess orders. Wholesalers, in response, also order more, amplifying the bullwhip effect throughout the supply chain. Ultimately, this overordering spreads to raw material suppliers, leading to inefficiencies and profit loss. Conversely, the bullwhip effect can also trigger when supply chain partners underestimate the popularity of a product, resulting in shortages. (Lee et., al 1997a.)

Lee et al. (2004) suggests that information sharing systems and collaboration are commonly employed strategies to mitigate the *Bullwhip effect.* Particularly, they note that the choice of forecasting method is linked to this phenomenon; selecting an appropriate forecasting method can enhance order forecasting accuracy and reduce the impact of the *Bullwhip effect* (Lee et al., 2004).

4.1.2 Demand Forecasting Method-Machine Learning

Researchers believe that coordination activities within the supply chain facilitate the flow of information, including production scheduling, inventory control, and delivery plans, among all stakeholders (Lee et al., 1997b). Additionally, as noted by Zhao et al., (2002), information sharing and integration among supply chain participants can help mitigate forecast errors and *Bullwhip effect*. (Zhao et al., 2002.)

Furthermore, Lee et al., (1997 b) suggests that new technological innovations based on real-time, accurate information sharing will help mitigate the *Bullwhip effect* (Lee et al., 1997b). Dutt et al., (2018) propose that implementing an effective demand forecasting mechanism and improved demand forecasting method, such as machine learning, can mitigate the *Bullwhip effect.* (Dutt et al., 2018.)

Machine learning is an emerging and advanced demand forecasting method that assists firms in creating more accurate demand predictions by handling complex interdependencies among numerous causal factors with non-linear relationship patterns affecting demand (Feizabadi, 2022). Consequently, it improves supply chain performance. (Feizabadi, 2022.)

The following section will provide an overview of machine learning, covering its various categories, the process of building and evaluating machine learning models, with the goal of understanding how to effectively utilize it for demand forecasting.

4.2 Machine Learning

ML can be defined in various ways, but the one that is widely recognized comes from Tom M. Mitchell (2018) who defined ML as follows.

> “*A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E*.” *(Dutt et al., 2018, Chapter 1.)*

Another well-known definition of machine learning is illustrated by Chollet (2017), presented as follows.

> *“A machine-learning system is trained rather than explicitly programmed. It is presented with many examples relevant to a task, and it finds statistical structure in these examples that eventually allows the system to come up with rules for the automating task.” (Chollet, 2018, 5)*

A short illustration of the machine learning process is presented in Figure 9 below.

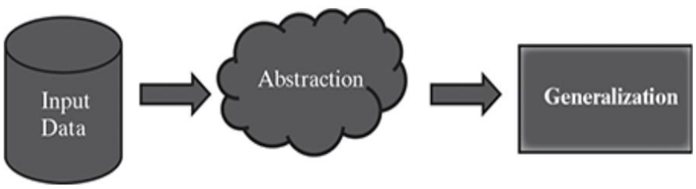


Figure 9. Process of machine learning (Dutt et al., 2018).

As seen in Figure 9, it presents the process of machine learning. In this process, experience refers to the historical data related to the task, which is utilized for future decision-making. The data is originally abstracted through various algorithms and will be fed into the system to form a framework to aid in decision-making afterwards (Dutt et al., 2018, Chapter 2.)

4.2.1 Machine learning development

Theodoridis (2021) believes that the roots of machine learning can be traced back to *statistics*, *computer science, information theory, signal processing,* and *automatic control,* all of which share the common characteristic of processing data. The commonly accepted evolution of machine learning is demonstrated in Figure 10 below.

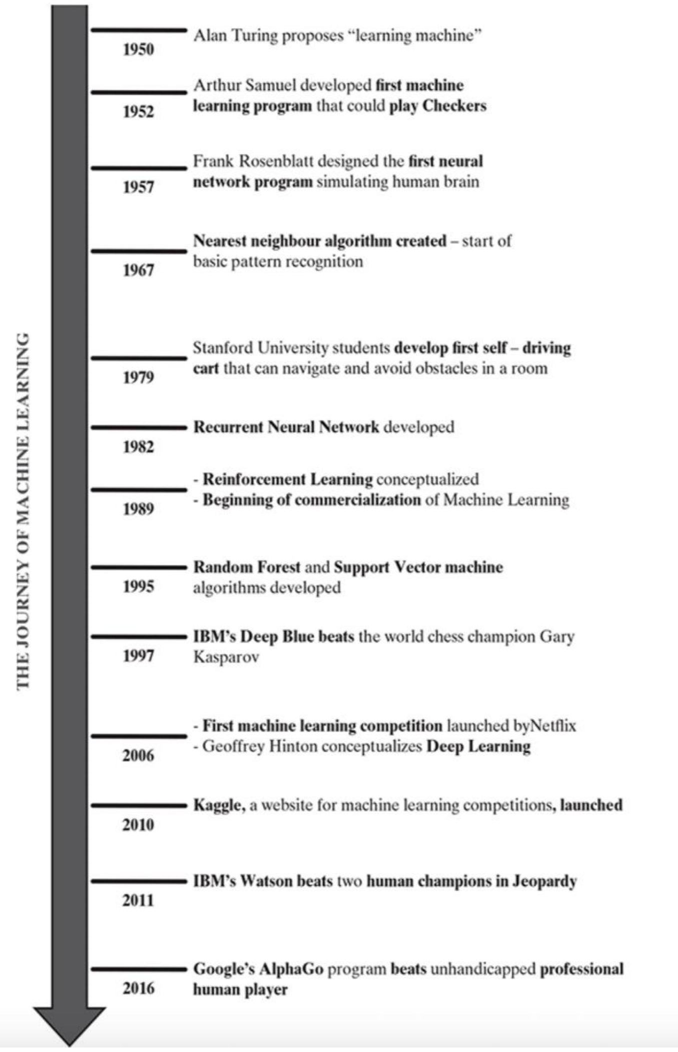


Figure 10. Machine Learning Evolution (Dutt et al., 2018).

As seen in Figure 10, in 1950, ML was first proposed by Alan Turing in his study where he raised the question "Can machines think?" or, in other words, "Do machines have intelligence?" His work was considered as the “real start of focused work in the field of machine learning.” (Dutt et al., 2018, Chapter 1.)

In 1952, ML was illustrated by Arthur Samuel as "the field of study that gives computers the ability to learn without being explicitly programmed”. (Ng,2023.) Samuel designed a game program for checkers. He required the computer to play many games against itself and watched which positions led to winning or losing. With time, the program learned what positions were good or bad and aimed for the good ones while avoiding the bad ones. Through this process, Samuel's program became increasingly adept at playing checkers. The computer demonstrated the determination to engage in tens of thousands of games against itself. (Ng, 2023.)

In 1957, Frank Rosenblatt developed the first neural network program simulating the human brain. Afterward, numerous algorithms were formulated by different researchers (Dutt et al., 2018, Chapter 1). In 1967, the Nearest Neighbor algorithm was created. This marked the beginning of basic pattern recognition. In 1982, the Recurrent Neural Network was developed. In 1995, the Random Forest and Support Vector Machine algorithms were developed. In 2006, the first machine learning competition was launched by Netflix, conceptualizing deep learning. In 2010, a website for machine learning was launched by Kaggle. It demonstrated the advancements in computer processing power since the early 2000s. Especially after 2010, computers have become increasingly capable of processing vast amounts of complex data and utilizing more sophisticated models. Since then, machine learning has experienced rapid development. (Theodoridis, 2021, Chapter 1.)

According to Ng (2023), machine learning is estimated to create an additional $13 trillion USD of value annually by the year 2030. It has become a mature technology utilized in every sphere of life, such as speech recognition, computer vision for Google Maps Street View images, recommending movies to audiences based on their preferences, and predicting future market trends to help businesses compete with uncertainty. (Ng, 2023.)

The following section will explore machine learning categories and recommend the most appropriate approach for the task at hand.

4.2.2 Machine learning categories

This section focuses on exploring the categories of machine learning. Before delving into the categories of machine learning, it is beneficial to clarify three concepts: artificial intelligence, machine learning and deep learning, as demonstrated in Figure 11 below.

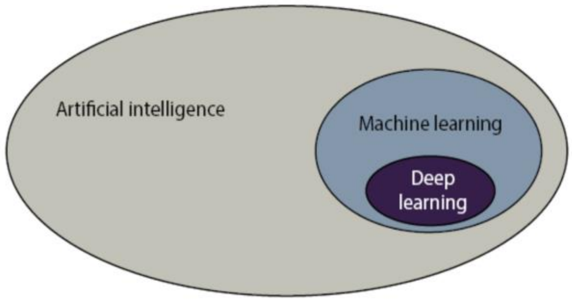


Figure 11. Artificial intelligence, Machine learning, and Deep learning (Serrano, 2021).

As seen in Figure 11, machine learning is the subset of artificial learning, and deep learning is the subset of machine learning. Artificial intelligence and machine learning share similarities, but they are not the same. Artificial intelligence is defined as "The set of all tasks in which a computer can make decisions." (Serrna, 2021, Chapter 1). Machine learning is defined as "The set of all tasks in which a computer can make decisions based on data." (Serrna, 2021, Chapter 1). Deep leaning is defined as follows.

> *"A new take on leaning representations from data that puts an emphasis on learning successive layers of increasingly meaningful from data that puts an emphasis on learning successive layers of increasingly meaningful representations."* (Chollet, 2018, 8.)

Machine learning can be classified into three primary types: supervised learning, unsupervised learning, and reinforcement learning demonstrated in Figure 12.

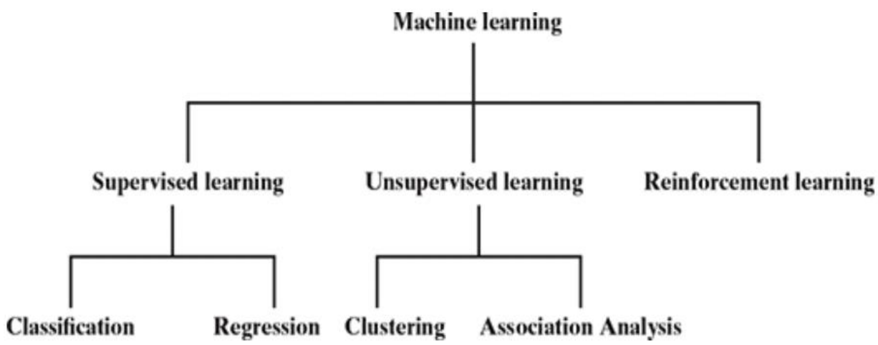


Figure 12. Machine learning types (Dutt et al., 2018).

As seen in Figure 12, in the realm of supervised learning, the categories encompass classification and regression. In unsupervised learning, the categories consist of clustering and association analysis. The explanation of each type will be provided as follows.

4.2.2.1 Supervised learning

Supervised learning is characterized by its reliance on labelled datasets which are designed to "supervise" algorithms in accurately categorizing data or forecasting outcomes. By utilizing labelled inputs and outputs, the model can assess its own precision and enhance its performance gradually through learning (Wang et al., 2023). Dino Esposito illustrated supervised learning in a simple manner: “To train the machine learning solution to accurately predict the output based on the input.” (Esposito, 2020, Chapter 2). An example of supervised learning is demonstrated in Figure 13.

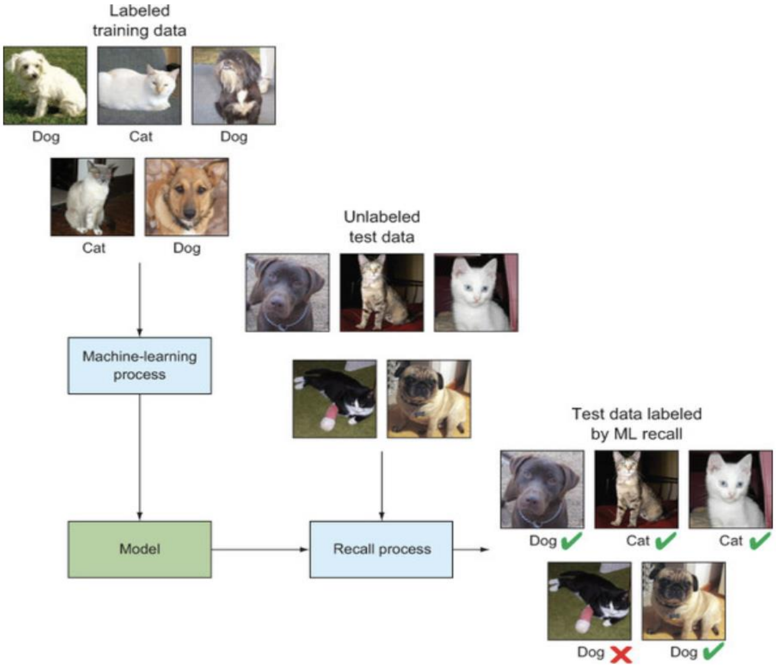


Figure 13. Supervised learning (Brink et al., 2016).

As seen in Figure 13, the labeled training datasets contain images of dogs and cats, with distinguishing features. For example, dogs typically have bigger ears and wag their tails, however cats have whiskers and fur. After feeding these datasets into the machine learning process, the model analyzes the features of dogs and cats and formulates a model or rule. When a new image or an unlabeled dataset is introduced, the model can recall its training and predict whether the image is of a dog or a cat (Serrano, 2021).

Supervised machine learning is divided into two groups: classification and regression. Each group encompasses different algorithms and is applied to different areas. Esposito and Brink respectively provide concrete demonstrations of this in their studies. To help clarify and understand the content, Table 6 is presented below.

Table 6. Supervised learning algorithm and application (based on: Brink et al., 2016; Dutt et al., 2018).

Supervised machine learning		
Type:	Classification	Regression
Algorithm:	Decision Tree, Random Forest, Support vector machine, Naïve bayes, Logistic Regression.	Linear regression, Multilinear regression, Polynomial regression, Nonlinear regression.
Application:	Spam and customer churn detection. Data ranking and sentiment analysis. Early diagnosis of a disease from medical images. A recommender system built for customers. News tagging. Fraud or fault detection.	Price prediction (houses, stocks, taxi fares, energy). Production prediction (food, goods, energy, availability of water). Income prediction. Time series forecasting. Demand forecasting in retail. Sales prediction for managers.

As seen in Table 6, the most common algorithms used for classification are “decision trees, random forests, support vector machines, naïve bayes, and logistic regression” (Esposito, 2020). Classification is used in various fields, such as: “spam and customer churn detection, data ranking and sentiment analysis; early diagnosis of diseases from medical images, recommender systems for customers, news tagging, fraud, or fault detection.” (Esposito, 2020, Chapter 3.)

The most common algorithms used for regression are linear regression, multilinear regression, polynomial regression, and nonlinear regression. Regression in machine learning is most used for: “Price prediction (houses, stocks, taxi fares, energy); Production prediction (food, goods, energy, availability of water); Income prediction; Time series forecasting; Demand forecasting in retail; Sales prediction for managers.” (Esposito, 2020, Chapter 3.)

4.2.2.2 Unsupervised Learning

Unsupervised learning encompasses various algorithms aimed at categorizing raw data without predefined labels. These algorithms analyze the data to uncover patterns and similarities, which are then utilized to categorize or organize the original data. These patterns are typically represented as clusters or labels, as illustrated in Figure 14. (Esposito 2020, Chapter2.)

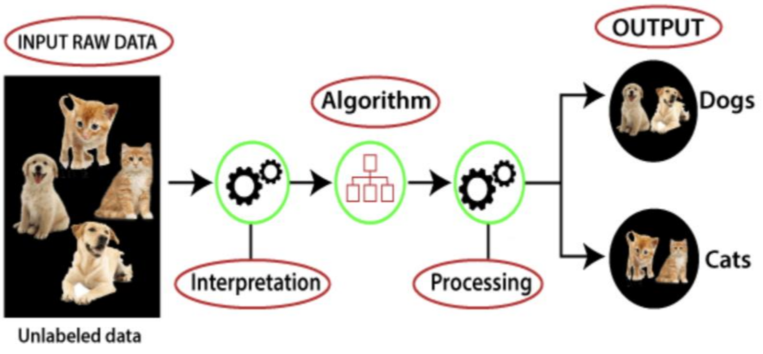


Figure 14. Unsupervised learning (Henrik Brink, 2016).

As seen in Figure 14, unsupervised learning differs from supervised learning. Its objective is to cluster unlabeled data by extracting information from the data and identifying similarities within it. When a set of unlabeled data containing images of dogs and cats is fed into the machine learning process, it interprets this information and finds similarities between the data points. The algorithm could then separate the dog images from the cat images, or even group them by breed. While machine learning may not understand which specific pets the images represent, it can distinguish the difference between dogs and cats and group them accordingly. (Serrana, 2021, Chapter 2.)

According to Dutt (2018), the primary type of unsupervised machine learning is clustering. The main algorithm and its application are presented in Table 7 below.

Table 7. The algorithm and application of Unsupervised machine learning (based on: Brink et al., 2016; Dutt et al., 2018).

Unsupervised machine learning	
Type:	Clustering,
Algorithm:	K-mean, Principal Component Analysis, Self-organizing map, Apriori algorithm, DBSCA etc.
Application:	Video recommendation, Market segmentation, medical imaging

As seen in Table 7, clustering is the primary type of unsupervised machine learning. It has the capability to distinguish and group similar unlabeled data to form clusters. The main algorithms used for unsupervised machine learning are listed as follows: *K-means, principal component analysis, self-organizing map, Apriori algorithm*, and *DBSCAN,* etc. Clustering is utilized to help address challenges in various business areas, such as video recommendation, market segmentation, and medical imaging. (Dutt et al., 2018, Chapter 1.5.2)

4.2.2.3 Reinforcement learning

Reinforcement learning is another type of machine learning. It differs from supervised and unsupervised learning. Figure 15 below is the demonstration of the reinforcement learning process.

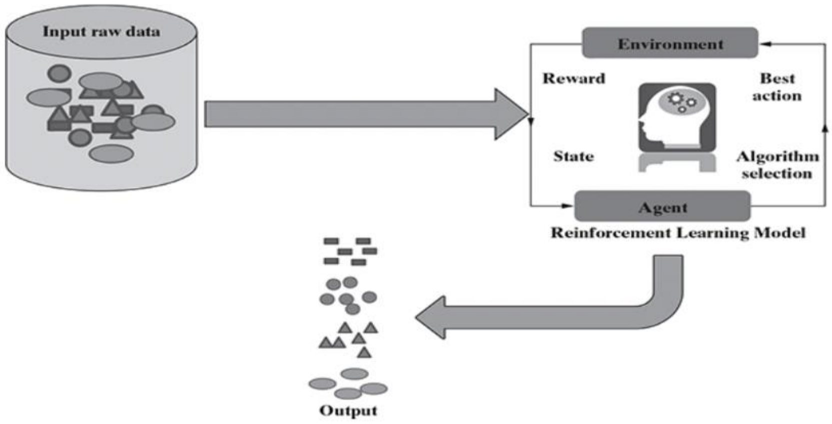


Figure 15. Reinforcement learning (Dutt et. al, 2018).

As seen in Figure 15, instead of feeding labeled or unlabeled data to the machine, an environment and agent are provided to the machine to complete the assigned task. An expected goal is set for this task. The environment will reward or punish the agent to assist it in reaching the goal (Serrano 2021, chapter 2). As Reinforcement Learning is based on environment, many parameters come into play. According to Nandy and Biswas (2018), Reinforcement Learning aims to achieve specific goals. “The environment in it is from the real world. The rewards usually come from the interaction with the environment which could be simulations such as 2D, or 3D or scenarios based on games.” (Nandy et al., 2018.)

The algorithms used for reinforcement learning encompass Q-learning and Sarsa. Practical applications include self-driving cars, intelligent robots, and AlphaZero, which is the latest version of DeepMind’s AI system. (Dutt et al., 2018, Chapter 1.5.4).

Based on the description of supervised, unsupervised, and reinforcement learning above, supervised learning emerges as the most appropriate method for this study. In the machine learning process discussed earlier, labeled data is fed into machine learning process for training, leading to the expected output. Therefore, the following section will explore the specific algorithm used in this study.

4.2.3 Machine learning algorithm

This section will explore the specific algorithms applied in this study. Before delving into the algorithms, it is crucial to distinguish between two key definitions: Model and Algorithm. These terms are often confused or interchanged. As defined by Luis and

Serrana (2021), a "Model" represents a set of rules that characterize the data and enable predictions. However, an "Algorithm" refers to the process used to construct the model. This section's objective is to identify the most suitable algorithms to aid in constructing the model for this study. (Serrano, 2021.)

4.2.3.1 Linear regression

In machine learning, linear regression stands out as one of the simplest algorithms for modeling relationships between features and labels within a dataset. Linear regression is a widely utilized and efficient technique for predicting various values, such as home prices, stock values, demand forecasting, and durations of video viewing or website engagement. (Esposito, 2020, Chapter 2.)

A regression model that fits well produces predicted values that closely align with the actual values. Therefore, a good regression model is characterized by minimal discrepancy between predicted and actual values (Dutt et al., 2018, Chapter 2). Figure 16 below illustrates an example of real estate value prediction solved through a linear regression model.

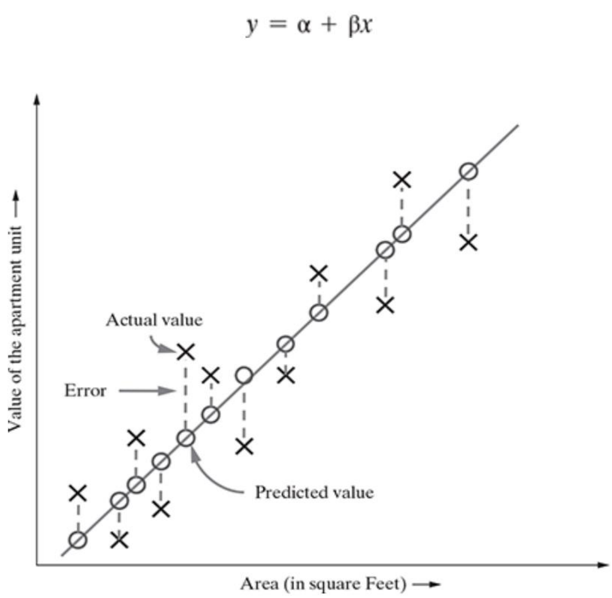


Figure 16. Linear regression model (Dutt et al., 2018).

As seen in Figure 16, If 'area' is the predictor variable (denoted as x) and 'value' is the target variable (denoted as y), the linear regression model can be expressed as follows:

"For a given x value, x̂, we predict y as ŷ, while the actual value of y is Y. The difference between the actual and predicted values, known as the residual, determines the fit of the regression model. A smaller residual indicates a better fit." (Dutt et al., 2018, Chapter 3.)

R-squared, also known as the coefficient of determination in both simple and multiple regression cases, is a valuable metric for assessing model fitness. Ranging from 0 to 1 (0%–100%), a higher R-squared value indicates a better fit. (Dutt et al., 2018, Chapter 3.) It is calculated as:

$$R^2 = \frac{SST - SSE}{SST}$$

Sum of Squares Total (SST) = squared differences of each observation from the overall mean = $\sum_{i=1}^{n} (y_i - \bar{y})^2$ where $\bar{y}$ is the mean.

Sum of Squared Errors (SSE) (of prediction) = sum of the squared residuals = $\sum_{i=1}^{n} (Y_i - \hat{y})^2$ where $\hat{y}_i$ Yi represents the actual value of yi, while yi denotes its predicted value. (Dutt et al., 2018, Chapter 3.)

4.2.3.2 Decision Tree

The decision tree stands as a fundamental machine learning algorithm. As noted by Vandeput (2021), decision trees create a tree map of inquiries to aid in predictions. They fall into two main categories: regression trees and classification trees. Regression problems entail estimating numerical outputs from diverse inputs, such as in forecasting. When decision trees are deployed to predict numbers, they are termed regression trees. The tree initiates predictions by asking questions, starting with choices of "yes" or "no," and proceeds accordingly until it arrives at a final prediction. Figure 17 below provides an illustrative example demonstrating the functionality of decision trees. (Vandeput, 2021, 223.)

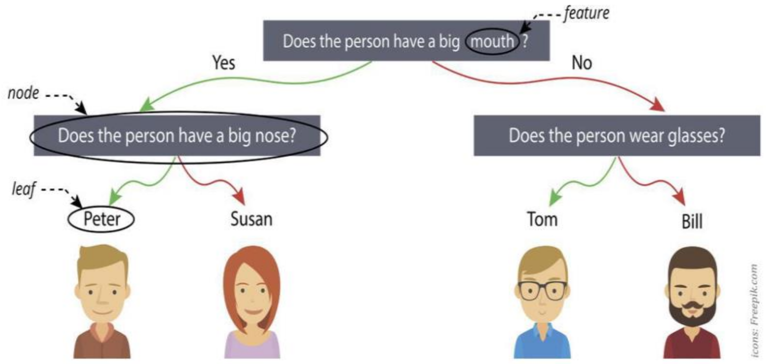


Figure 17. Decision Tree (Vandeput, 2021).

As seen in Figure 17 decision tree, each question serves as a node. For instance, on the left, the query "Does the person have a big nose?" forms a node, while its corresponding answer constitutes a leaf, representing an individual. Since many individuals might have both big noses and big mouths, a leaf may hold multiple values. The tree holds a plethora of information, with each node representing a feature utilized by the model for predictions. (Vandeput, 2021, 222-228.)

4.2.3.3 Recurrent neural networks

A Recurrent Neural Network (RNN) is a subset of deep learning tailored for sequential data processing, encompassing time series, text, speech, and video. Equipped with a memory mechanism, RNNs retain information from previous inputs to enhance predictive accuracy. (Kostadinov, 2018.)

Carbonneau et al., (2008) emphasizes the significance of Recurrent Neural Networks (RNNs) in addressing practical issues, particularly in predictive tasks involving time series data. In his research, he utilizes RNNs as an advanced demand forecasting technique, as illustrated in Figure 18 below.

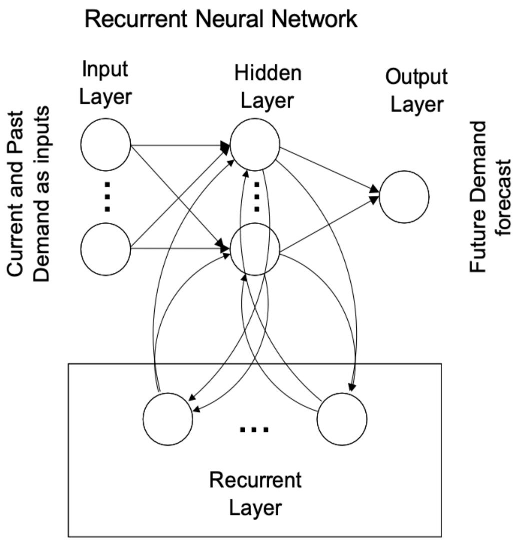


Figure 18. Recurrent neural network for demand forecasting (MathWorks, 2000. Cited in: Carbonneau et al., 2008).

As seen in Figure 18, Recurrent Neural Networks (RNNs) exhibit recurrent connections where each “neuron in the hidden layer feeds back into all neurons of the same layer” in the subsequent step. This mechanism enables RNNs to discern temporal patterns effectively. RNN architectures employed a hyperbolic tangent transfer function. In the simulation utilizing synthetic data, six neurons comprised the hidden layer, with a learning rate of 0.01 and a momentum of 0.7. For the RNN tailored for foundry demand forecasting, a two-neuron hidden layer was chosen to maintain a favorable ratio of samples to weights at 6.5. Results demonstrate its superior accuracy compared to other forecasting methods in the experiments. (Carbonneau et al., 2008.)

4.2.3.4 Support vector machine

The Support Vector Machine (SVM) algorithm can handle linear and nonlinear problems effectively. Its strong theoretical basis and flexible practicality make it suitable for use in a wide range of situations. (Brink et al., 2016, Chapter 3.)

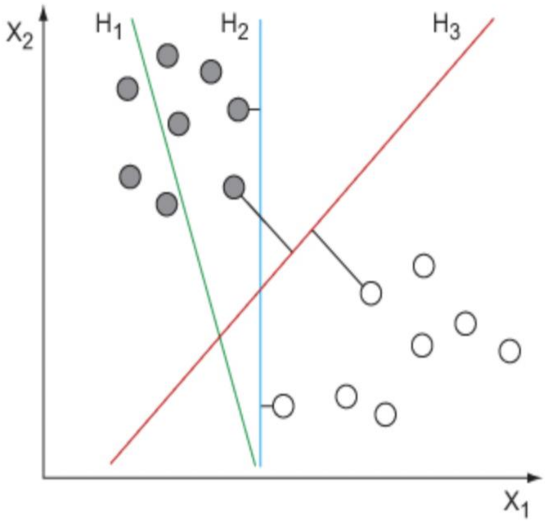


Figure 19. Support vector machine (Brink et al., 2016).

As seen in Figure 19, Support Vector Machines (SVMs) aim to identify the “widest margin between the points situated on either side of the decision boundary”, instead of assessing the distance to every single point. The rationale behind this approach is to prioritize points that are in proximity to the boundary rather than those well within it. It's evident that boundary lines H1 and H2 are inadequate as they do not maximize the distance to the closest points on both sides. On the contrary, H3 represents the optimal boundary line. (Brink et al., 2016, Chapter 3.)

Summing up, in this section, four machine learning algorithms: *linear regression, decision tree, recurrent neural networks, and support vector machines* were introduced. The objective of ML algorithms is to identify patterns and relationships with historical training data. It also learns from the data to create models that can accurately predict important attributes in new datasets (Brink et al., 2016, Chapter 2). Hence, the next step is to prepare the data which is a key aspect of the machine learning process.

4.2.4 Data preparation

Machine learning's effectiveness is significantly influenced by data quality (Dutt et al., 2018). Therefore, this section will focus on optimizing data preparation, encompassing three key steps: data collection, preprocessing, and visualization. To aid understanding, Figure 20 below presents a basic machine learning workflow.

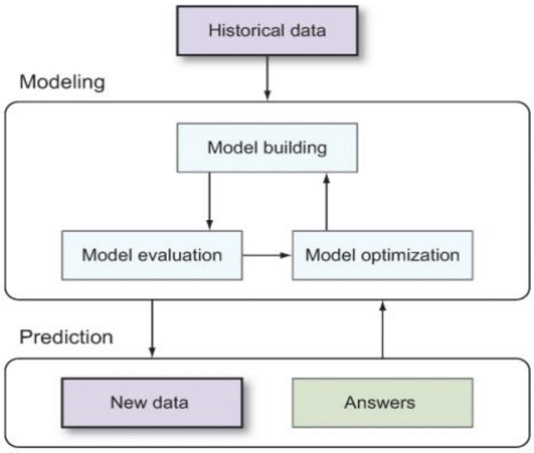


Figure 20. Basic machine learning workflow (Brink et al., 2016).

Figure 20 illustrates that historical data, which is the first step in the workflow, determines the effectiveness of subsequent steps: model building and prediction, echoing Herink Brink's observation.

> "*Training data, therefore, is fundamental in the pursuit of machine learning. With high-quality data, subtle nuances and correlations can be accurately captured and high-fidelity predictive systems can be built. But if training data is of poor quality, the efforts of even the best ML algorithms may be rendered useless*." (Brink et al., 2017, Chapter 2.)

4.2.4.1 Data collection

At the data collection stage, the objective is to grasp several key concepts: Firstly, determining the appropriate method for incorporating data features. Secondly, establishing the appropriate quantity of data.

Data often encompasses numerous features. It is important to employ a framework to determine which should be retained. Herink suggests two key criteria for this selection. Firstly, only features presumed to be linked to the target variable should be included; irrelevant features must be excluded. Secondly, features must be either numerical or categorical. Non-numerical data should be converted into numerical format through feature engineering for inclusion. (Brink et al., 2016, Chapter 2.)

Determining the optimal amount of data to build a model presents a formidable challenge with no definitive answers. Brink (2016) suggests several criteria to consider. Firstly, it's essential to evaluate the complexity of the problem. It needs to distinguish between simple and complex patterns in the dataset. Secondly, the required level of accuracy also influences the quantity of data needed; achieving 95% accuracy typically demands more data compared to achieving 60% accuracy (Brink et al., 2016, Chapter 2). Figure 21 below illustrates the correlation between training times and accuracy.

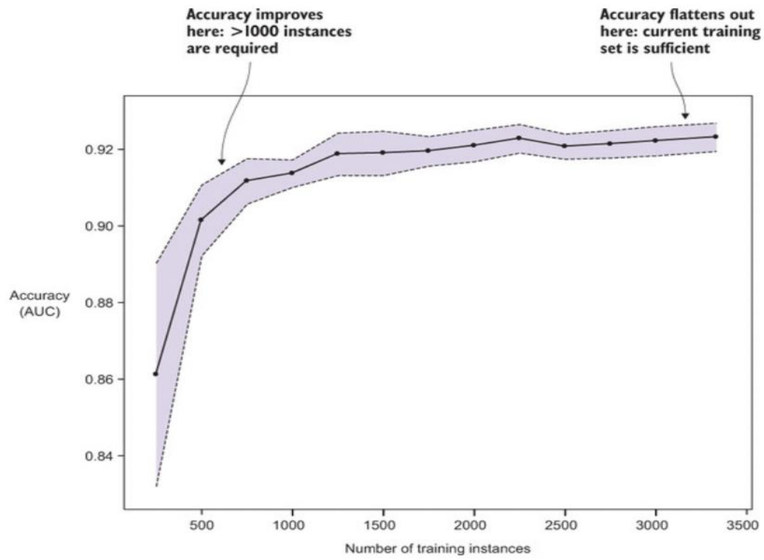


Figure 21. Number of training instances (Brink et al., 2016).

As seen in Figure 21, the variation in accuracy of the machine learning model depends on the number of training instances utilized. It becomes evident that as more training data is added, the ML model shows enhancement. The training times from 250 to 500 to 750 leads to notable increases in accuracy. However, after surpassing 2,000 training times, the accuracy levels do not demonstrate notable increase in accuracy. This indicates that more training might not enhance the ML model's performance. Nevertheless, significant enhancements could still be achieved by incorporating more features. (Brink et al., 2016, Chapter 2.)

4.2.4.2 Preprocessing the data

Once data collection is finalized, the subsequent step involves data preprocessing. This typically encompasses categorizing features, handling missing data, and conducting feature engineering, tailored to the data's type and structure. Each of these steps will be illustrated below.

4.2.4.3 Categorizing features

Certain machine learning algorithms exclusively operate on numerical data, including integers and real-valued numbers. In such scenarios, non-numerical features must be transformed into appropriate representations. An example is provided below.

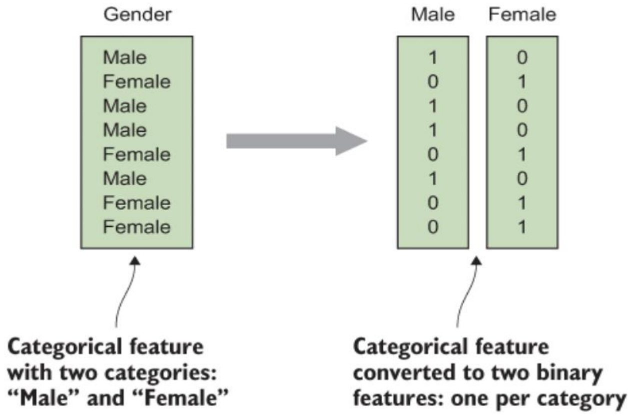


Figure 22. Categorical columns converted to numerical columns (Brink et al., 2016).

As seen in Figure 22, it presents a categorical feature in the left column, comprising two categories: male and female. To enhance the comprehension of this data by machine learning algorithms, it is advisable to convert it into the two columns on the right: a set of binary features, each representing one category.

4.2.4.4 Dealing with missing data

Missing data typically appears as either a blank cell or designated as 'not a number' (NaN). It is important to distinguish between these two types of missing values and handle them accordingly. Brink et al., (2016) proposed a comprehensive decision diagram for managing missing values during data preparation for machine learning modeling, illustrated in Figure 23.

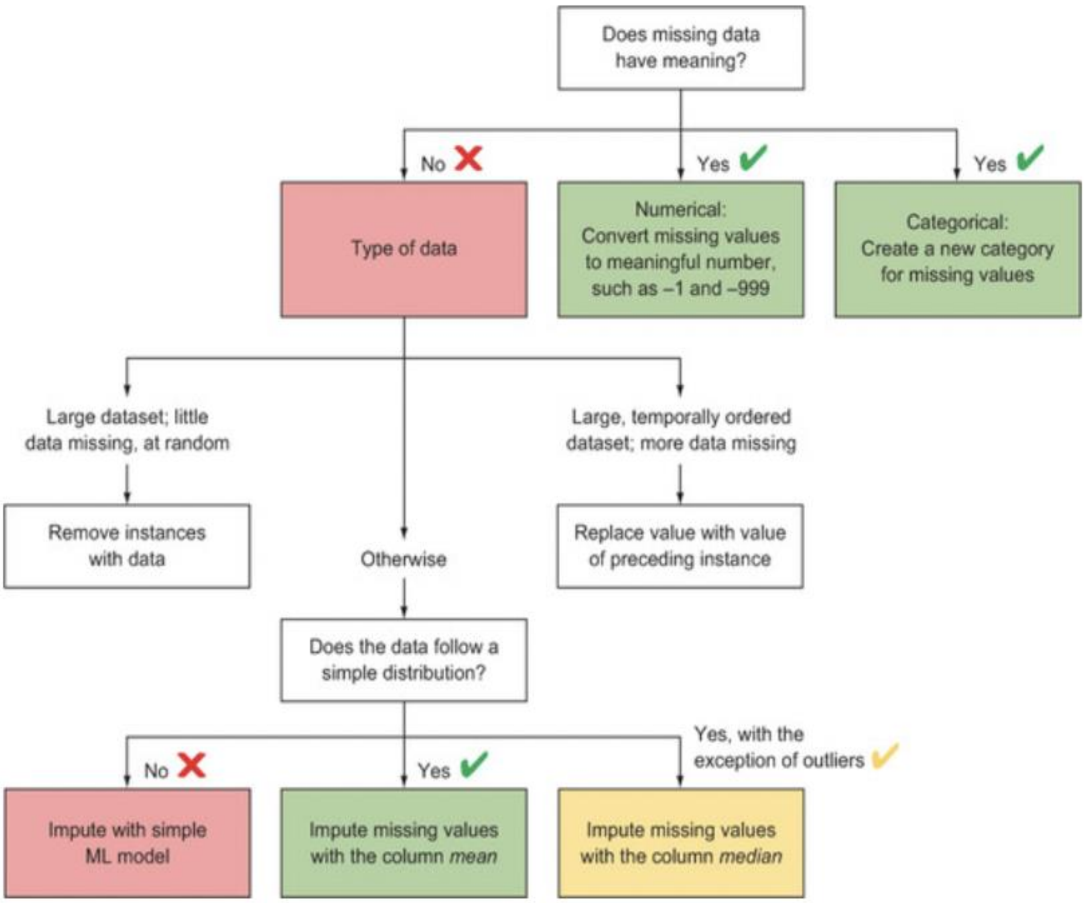


Figure 23. Dealing with missing data (Brink et al., 2016).

In Figure 23, two types of missing data are observed: one with significance for the target output and the other without. Processing meaningful data is straightforward. One approach is to create a distinct category recognizable by machine learning algorithms. Alternatively, missing values can be replaced with meaningful placeholders such as -1 or -999. Dealing with meaningless missing data is more complex and depends on various scenarios. For instances where only a small portion of the dataset is missing, it may be feasible to simply remove that data. However, in the scenario where a massive portion of the dataset is missing, it is advisable to replace missing values with those from preceding data. In the final scenario, if the missing data lacks significance and the dataset is not substantial, yet adheres to a straightforward distribution, the recommended solution involves imputing the missing data with the column mean. (Brink et al., 2016, Chapter 2.)

4.2.4.5 Feature engineering

“Feature engineering is the process of applying mathematical transformations to raw data to create new input features for ML modeling” (Brink et al., 2016, Chapter 5). Feature engineering simplifies data cleaning, a crucial process for effective machine learning. Messy data can hinder model performance and prediction accuracy. Transformations involved can vary from basic to highly intricate.

During feature engineering, there are numerous recommendations for applying transformations, including feature selection, which involves identifying the most relevant attributes from a large dataset. Forward selection entails a process of feature selection where features are progressively incorporated one by one. It effectively enhances the model's accuracy. Conversely, "backward elimination" involves removing the feature that most significantly decreases the model's accuracy, based on the present selection of active features. (Brink et al., 2016, Chapter 5.)

Brink et al., (2016) emphasizes that historical demand data belongs to the category of time series data. Classical time series data comprises numerical measurements collected cross time intervals. This raw data can be organized into various classical time series formats, such as yearly, monthly, or daily aggregates. (Brink et al., 2016, Chapter 5). Therefore, this thesis will follow his recommendation when prepressing and cleaning the historical demand data.

4.2.4.6 Data Visualization

Data visualization is a widely employed technique in data preparation. It serves two primary roles: guiding model development and aiding in comprehension of the target output. Additionally, visualized data illustrates the composition of the training set and highlights any missing datasets. Figure 24 below is one example for demonstrating data visualization.

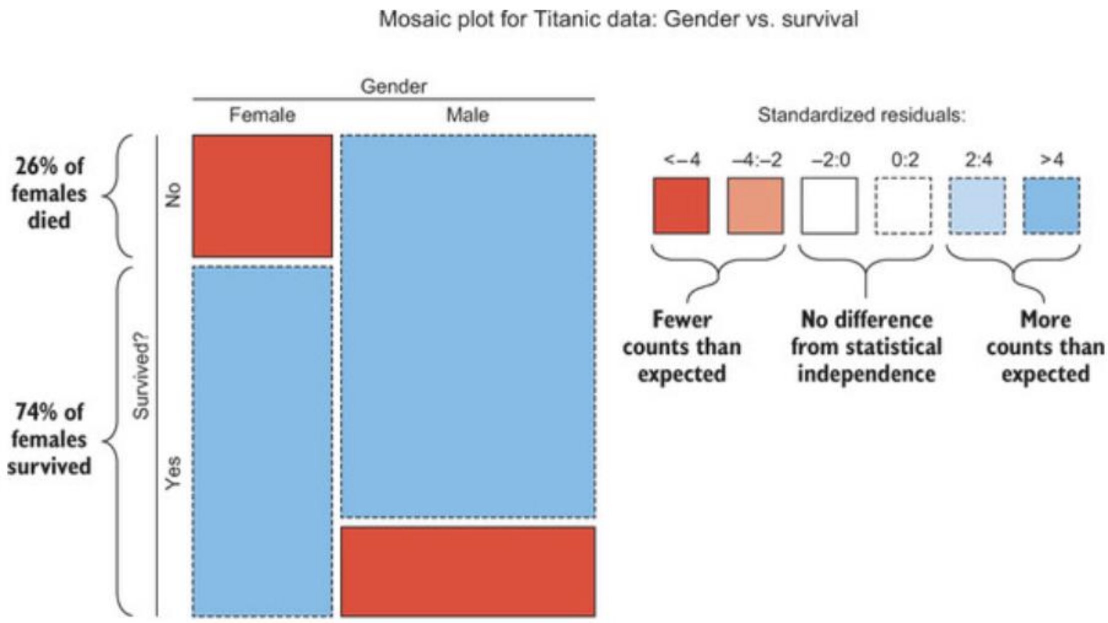


Figure 24. Data visualization technique (Brink et al., 2016).

Figure 24 illustrates the Mosaic plot technique. It presents the correlation between gender and survival rates aboard the Titanic. The visualization distinctly indicates a significantly higher survival rate among females compared to males, challenging the assumption of gender-independent survival. This observation aligns with the historical maritime principle of "Women and children first." (Brink et al., 2016, Chapter 3.)

During this thesis's data preparation phase, this technique will be used to show the correlation between product demands and their respective part numbers.

4.2.5 Modeling and modeling evaluation

This section describes modeling, and modeling evaluation. According to Dutt et al., (2018) upon the data is prepared for modeling, the learning process will start, First, the input data is divided into training data and test data. This step is relevant solely for supervised learning. Next, it will proceed to model selection. It means to explore various models or learning algorithms to determine the most appropriate one. Finally, it is training and application. It means to train the model by using the training data and relevant algorithms. After it will be applied to unknown data (Dutt et al., 2018). To aid understanding, one machine learning model build process is presented in Figure 25 below.

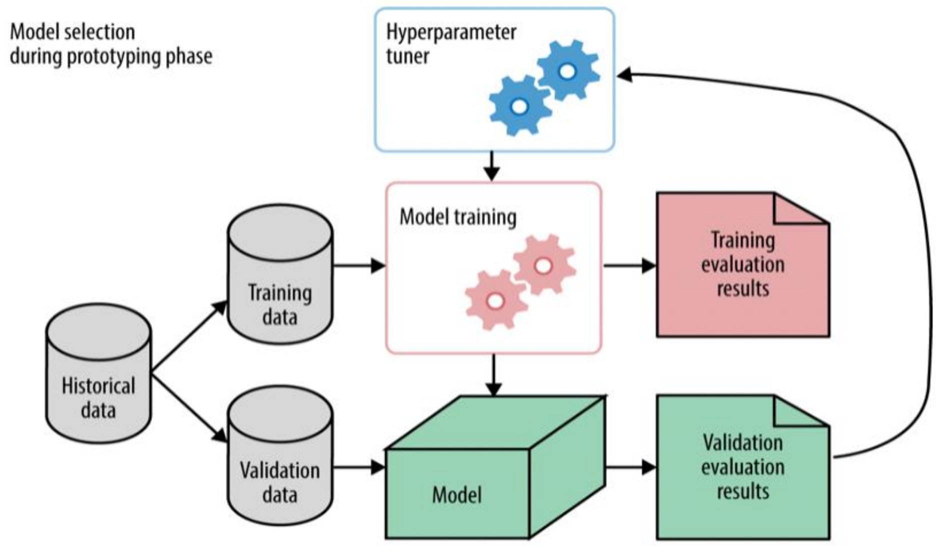


Figure 25. The prototyping phase of building a machine learning model (Zheng, 2015).

In Figure 25, the historical data is initially categorized into two types: training data and validation data. The training data is utilized to teach the machine and enable it to discern patterns. The outcome is to generate an ML model. The model's efficacy is assessed by using validation data. Based on the validation evaluation outcomes, adjustments are made to the hyperparameter tuner to produce a more fitting model. (Zheng, 2015, Chapter 3.)

In a nutshell, the initial phase should involve data preprocessing for the demand forecasting of the case company. Following that, supervised machine learning techniques, including several algorithms, can be employed to train the data.

4.2.5.1 Overfitting and solution

Overfitting and Underfitting are common problems in machine learning. It can impact the performance of machine learning models. It is important to understand the meanings of overfitting and underfitting to build a good machine learning model. Figure 26 below shows three scenarios.

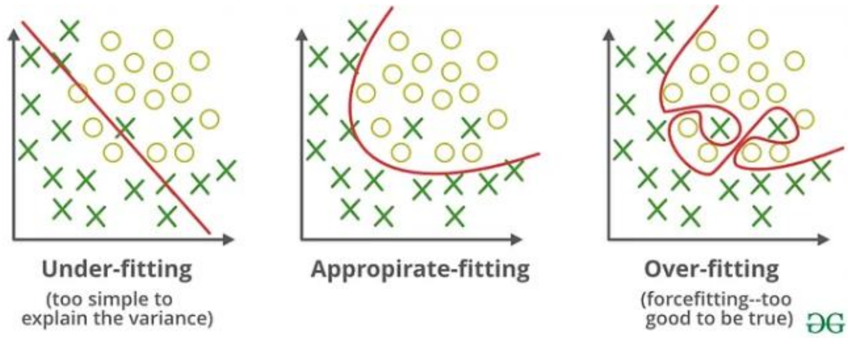


Figure 26. Overfitting and underfitting (Greeksforgreeks, 2024).

In the left side of Figure 26, the machine learning model is too simple, it did not illustrate the training dataset, so it is called underfitting. Underfitting is caused by the model with few parameters or by leveraging a simple ML algorithm. To solve the under-fitting problem, either a model with more parameters should be used, or a more powerful machine learning model should be chosen. In the right side of Figure 26, the machine learning model is too complicated compared to the training dataset, it is called overfitting. This can be solved by either changing to a model with less parameters or by changing to a simpler machine learning model. In the middle part of Figure 26, a well-trained dataset is shown, so the machine learning model is an appropriate fitting.

4.2.5.2 Machine learning evaluation metrics

According to Zheng (2015), various metrics are employed to evaluate machine learning models (Zheng, 2015, Chapter 2). This thesis will focus on supervised machine learning. The main metrics are shown as follows.

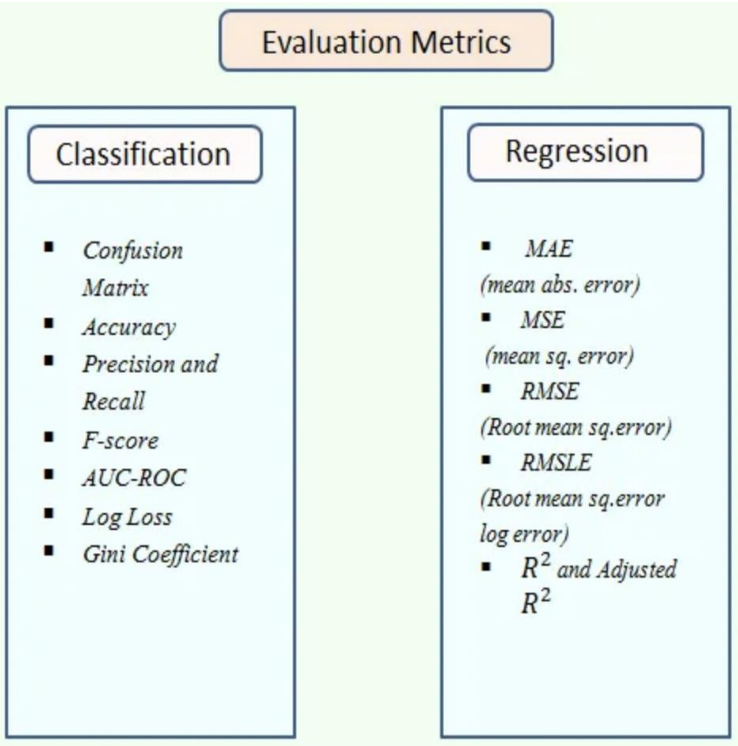


Figure 27. Machine learning Model Evaluation metrics (Ladkar, 2020).

Figure 27 displays metrics for evaluating classification and regression models. Metrics in the left box are used for classification models. Evaluation. Those in the right box are used for regression models evaluation. The commonly used metrics are illustrated below.

Accuracy is to evaluate how frequently the classifier accurately predicts outcomes. It is calculated by dividing the number of appropriate predictions by the total number of predictions. This represents the portion of data points in the test set. (Zheng, 2015, Chapter 2). Accuracy is also calculated from a confusion matrix using the following formula. (Kulkarni et al., 2021.)

Accuracy= $\frac{TN+TP}{TN+FP+FN+TP}$

Precision and *recall* are popular metrics for classification problems. Precision indicates how accurately the model predicts positive outcomes. Recall assesses the model's ability to capture all positive instances. In Python, it can calculate precision and recall by using the "precision_score()" and "recall_score()" functions. (Kulkarni et al., 2021.)

The formulas for precision and recall calculation are provided below.

$Precision = TP\ Recall = TP\ TP + FP\ TP + FN.$

“An ROC curve serves as the primary method for representing the binary classifier, while AUC stands out as a top choice for the numerical measure. “(Markham, K,2014). ROC curve is utilized for assessing classification models' effectiveness. The False Positive Rate (FPR) can be found on the horizontal axis. The True Positive Rate (TPR) can be found on the vertical axis. The classifier operates over a range of thresholds spanning from 0 to 1 to perform classification. At each threshold, the corresponding FPR and TPR values are plotted. Figure 28 below is presented an illustration of a typical ROC curve. (Kulkarni et al., 2021.)

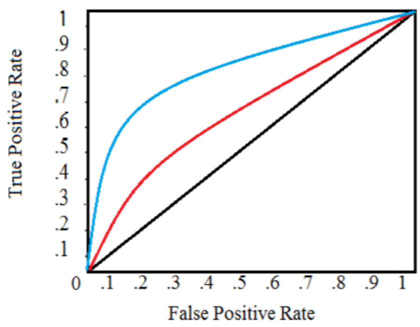


Figure 28. ROC CURVE for binary classifier (Ladkar, 2020).

As seen in Figure 28, it presents an ROC curve. The red test lies closer to the diagonal line. It indicats lower accuracy compared to the blue test.

Next, AUC is the area that is presented in Figure 29 below. This demonstrates that when the area under the ROC curve (AUC) is higher, it will present a more effective classifier. A perfect classifier achieves an AUC of 1. Optimal classifier performance occurs when the model selects a threshold value that yields a true positive rate (TPR) close to 1, and it also maintains a false positive rate (FPR) near 0. (Ladkar, 2020.)

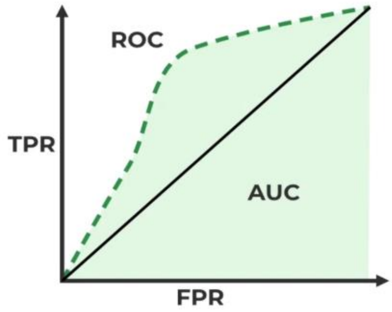


Figure 29. ROC-AUC Classification Evaluation Metric (Geeksforgeeks, 2024).

Compared to classification models, regression models are used for predicting a continuous numerical value. Due to the difference in the target variable, the evaluation metrics for regression and classification models also differ (Zheng, 2015). In the field of regression model, the most used evaluation metrics are MAE and RMSE.

In machine learning, “the *Mean Absolute Error (MAE)* is a widely utilized measure to assess the average absolute deviation between the actual and predicted values” (Bernico, 2018). The formula for MAE is as follows:

$$\text{MAE} = \frac{1}{n}\sum_{j=1}^{n} \left| y_j - \hat{y}_j \right|$$

Where:

y_j represents true or false value,

$\hat{y}_j$ represents predicted value, and

"n" is the total count of observations in the dataset.

RMSE (Root Mean Squared Error) is a metric to assess the precision of predictive models. It is applicable when predictions entail continuous numerical values (Bernico, 2018). Its formula for a dataset comprising 'n' data points is shown as follows:

RMSE = $\sqrt{\frac{1}{n}\sum_{j=1}^{n}(y_j - \hat{y}_j)^2}$

Where:

y_j represents the actual value,

$\hat{y}_j$ represents the predicted value, and

N denotes the total count of observation in the dataset.

4.2.5.3 Machine learning model evaluation methods

The *hold out validation* and *k-fold cross-validation are* two common evaluation methods in ML. They are shown in Figure 30 below.

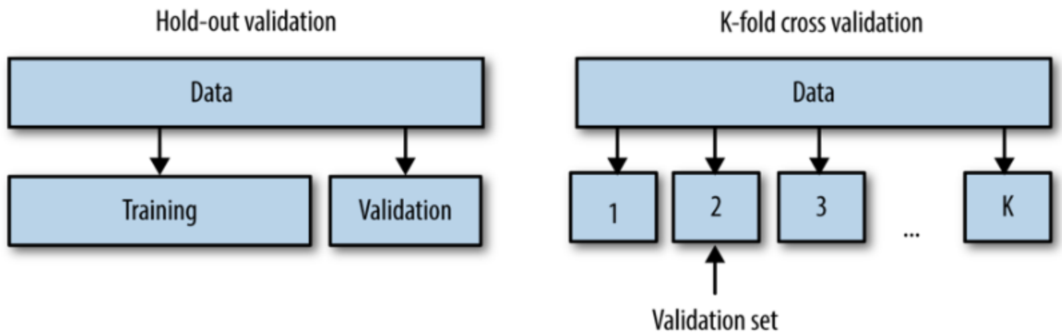


Figure 30. Hold-out validation and K-fold cross validation (Zheng, 2015, Chapter 3).

As seen in Figure 30, the left one is the Hold-out validation method, and the right one is K-fold cross validation method. Hold-out validation is described as follows. Historical data is split into two categories. One is training data, and another is for validation data. In the Hold-out validation method, 80% of historical data is for training. The remaining 20% for testing. In contrast, K-fold cross-validation involves randomly dividing the historical data into K groups. After that one group is served as the training data and the others are used for testing and validation.

An example is presented in Figure 31 below. (Zheng, 2015 & Allibhai, 2018.)

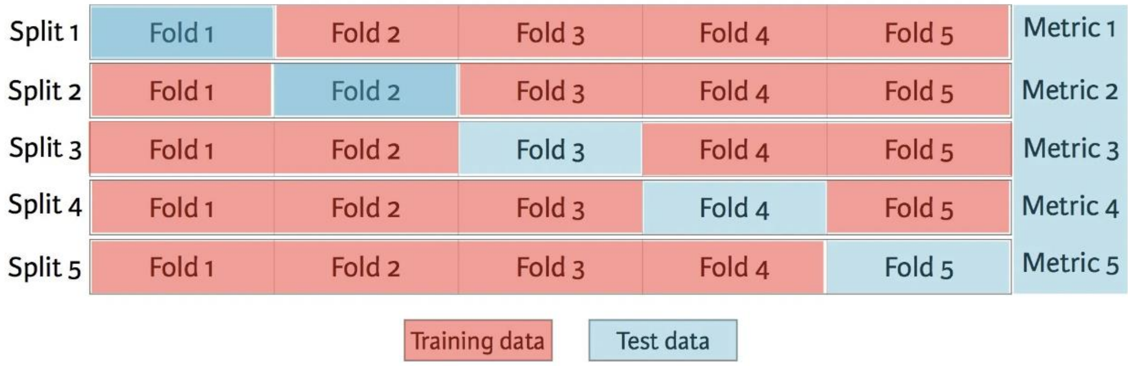


Figure 31. K-fold cross validation (Allibhai, 2018).

Figure 31 displays that the dataset includes 5 groups which contains both training and testing data. Firstly, Fold 1 is used to train the model, and the other 4 folds are used to test how well the model performs. This process is repeated for each fold. Finally, every group will be served as both the training and testing set.

However, the hold-out method relies on historical data. It often contains a substantial dataset. Its drawback is its reliance on how the data is partitioned. Sometimes it will affect accuracy. In contrast, Cross-validation is typically favored due to its provision of multiple train-test splits. It provides a better understanding of how well the model performs on data it has not seen before. (Alibhai, 2018.)

This section has covered all the foundational theories for building and evaluating machine learning models. The next section will shift towards machine learning applications in demand forecasting.

4.3 Machine Learning applied in Demand Forecasting

This section aims to present the process of building a ML model for demand forecasting. First, it begins by introducing the primary algorithm typically employed in demand forecasting. After this, it highlights the process for constructing the Machine Learning model for demand forecasting. Lastly, it presents a tool tailored for machine learning systems. It will improve the interaction between data, stakeholders, and the value proposition.

4.3.1 Machine Learning Model applied in Demand Forecasting

This task employs four ML models: Linear Regression, Decision Tree, Recurrent Neural Network, and Support Vector Machine. Each model will be illustrated as follows.

4.3.1.1 Linear Regress model

Vandeput (2021), highlights numerous Python libraries offering models for computing linear regressions in demand forecasting. He illustrates his model using an example highlighted in Figure 32.

```
from sklearn.linear_model import LinearRegression
reg = LinearRegression() # Create a linear regression object
reg = reg.fit(X_train,Y_train) # Fit it to the training data
# Create two predictions for the training and test sets
Y_train_pred = reg.predict(X_train)
Y_test_pred = reg.predict(X_test)
```

Figure 32. Linear regression model example (Vandeput, 2021).

In Figure 32, the model named 'reg' is created and fitted to the training data (X_train, Y_train). He utilized the method. fit () to train his model and generated predictions based on X_train and X_test using the method to predict. (Vandeput, 2021, 216.)

4.3.1.2 Decision Tree Model

To demonstrate how the decision tree works for demand forecasting, Vandeput (2021) also gives the example employed in the demand forecasting by using the dataset presented in Figure 33 below.

X_train				Y_train	Is the first demand observation >7?
5	15	10	7	6	No
15	10	7	6	**13**	**Yes**
10	7	6	13	**11**	**Yes**
7	6	13	11	5	No
6	13	11	5	4	No
13	11	5	4	**11**	**Yes**
11	5	4	11	**9**	**Yes**
7	2	3	1	1	No

Figure 33. Decision tree dataset (Vandeput, 2021).

As seen in Figure 33, the question posed is: "Does the initial demand observation exceed 7?" This response acts as a predictor for the coming quarter. Positive responses indicate a high demand (≥8), while negative responses suggest a probable low demand (≤7). The algorithm aids in expanding the decision tree at each node by querying one of the available features, such as the demand from previous quarters, until the criteria are met. (Vandeput, 2021, P223.)

4.3.1.3 Recurrent neural networks Model used for Demand forecasting.

As discussed earlier in the section on machine learning algorithms, Carbonneau et al. (2008) demonstrated that Recurrent Neural Networks is a suitable method for demand forecasting tasks.

Muhaimin et al., (2021) proposed that *RNN* was one of the most effective methods for forecasting intermittent demand data. It is presented below:

This approach ensures that the output value remains positive because of the *ReLU and sigmoid activation* functions used in *RNN*. Moreover, *RNN* is good at predicting intermittent data. It displays dynamic values, and effectively tracks testing data in its forecast process. Furthermore, RNN allows adjustments such as the number of hidden layers, recurrent activation function, and other configurations. Training data with RNN may require more time, especially when fine-tuning parameters are necessary. “Despite similar error measurements, this method yields superior forecast results due to its ability to closely match the testing data.” (Muhaimin et al., 2021.)

4.3.1.4 Support Vector Machine Model used for Demand Forecasting.

Carbonneau (2008) introduces the *Support Vector Machine (SVM)* algorithm as an advanced approach for demand forecasting in his experiment. The results presented SVM as one of the most effective forecasting techniques in his study. (Carbonneau et al., 2008.) The experiment results show that the performance of SVM is superior to other models. The model will lead to fewer sales failures and lower inventory levels.

Villegas and colleagues (2018) introduce an innovative approach by utilizing *Support Vector Machine (SVM)* for demand forecasting. Their methodology involves the identification of the optimal forecast model. The results show that the SVM-based model demonstrates notable enhancements in forecasting accuracy, bias reduction, and effectiveness. (Villegas et al., 2018.)

In summary, the four ML models discussed above will be employed for demand forecasting to accomplish the given task. The next section will introduce the process of ML applied in demand forecasting.

4.3.2 Process of Machine learning applied in demand forecasting.

As highlighted by Adnan et al. (2021), accurate demand forecasting has a crucial impact in empowering companies to make the correct decisions and driving them towards success. When equipped with precise demand forecasts, companies can confidently "navigate their product offerings and target markets, fostering stronger decision-making processes, improves customer satisfaction, optimizes supply chain operations, and boosts profitability." (Adnan et al., 2021).

In their research, he and his partners explored two ML models for demand forecasting. Their study demonstrated that employing these two models can lead to higher forecast accuracy and minimized errors. It also explores an ML-based process for demand forecasting. The process is shown in Figure 34 below.

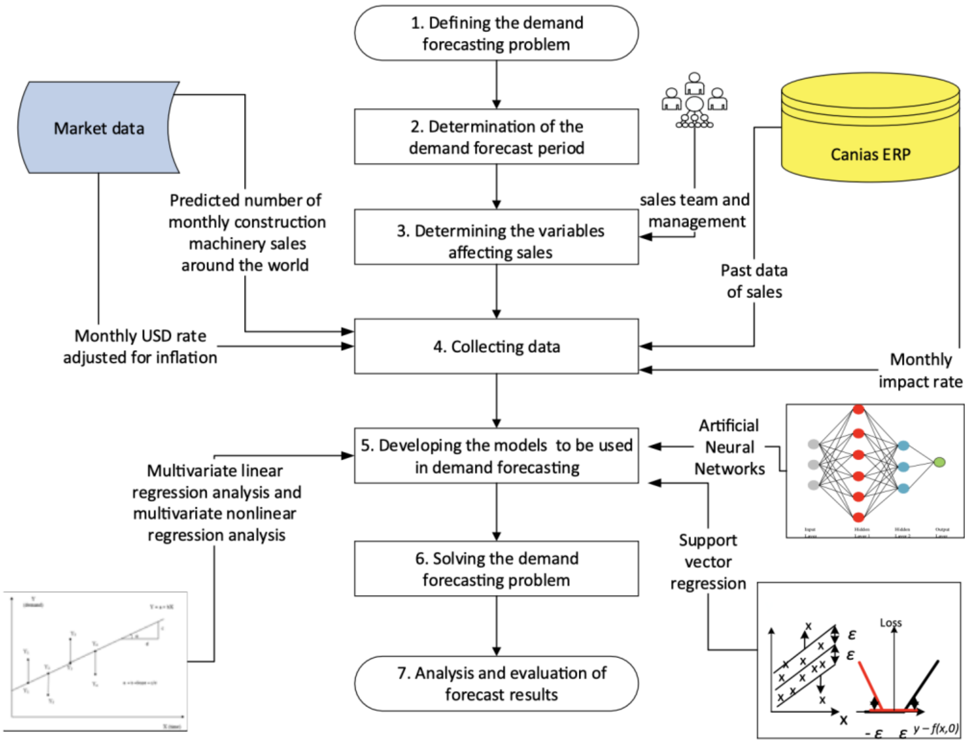


Figure 34. Process of Machine Learning applied in Demand Forecasting (Andan et al., 2021).

As illustrated in Figure 34, the process of machine learning applied in demand forecasting includes 7 phases. First, the primary task is to define what the firm is trying to predict in demand forecasting. Then, it needs to decide the period the firm will forecast for. Next, it will identify all the important elements that might affect sales, such as involving sales and management teams to make sure it does not miss anything important. (Andan et al., 2021.)

Following this phase, the fourth phase involves the collection of data from two sources. One is from Market data which encompasses monthly construction machinery sales and monthly USD rate adjustments for inflation. Another data is extracted from Enterprise Resource Planning (ERP) systems. (Andan et al., 2021.)

The fifth stage involves the development of sophisticated machine learning models. Two ML algorithms are used in this process to build the model, including Artificial *Neural Networks* and *Support Vector Regression* techniques. Additionally, traditional methodologies such as multivariate linear regression and non-linear regression analysis are used as reference for model evaluation and benchmarking. (Andan et al., 2021.)

After ML models are built, the next step is to use them for forecasting. It utilizes the computational power of these models to make predictions about the future demand. It aims to improve accuracy in forecasts. (Andan et al., 2021.)

Finally, at the end of this process, it analyzes and evaluates the forecasted results. By carefully examining the outcomes, it demonstrates how effective the models are and indicates areas where they can be improved. This evaluation helps the firm make the demand forecasting better over time. (Andan et al., 2021.)

4.3.3 Machine Learning Canvas

The ML Canvas is “a framework to connect the dots between data collection, machine learning, stakeholders, and value creation” (Dornard, 2016.) Dornard (2016) designed a ML canvas inspired by the Business Model Canvas to visually represent all the elements of machine learning to stakeholders. He believes the machine learning canvas is invaluable for aligning stakeholders at the outset of an experiment, fostering a shared understanding of predictions and the value derived from the model. By framing the machine learning problem beforehand, it facilitates comprehension of end-users and consideration of their pain points prior to implementation (Dornard, 2016). A machine learning canvas template is presented in Figure 35 below.

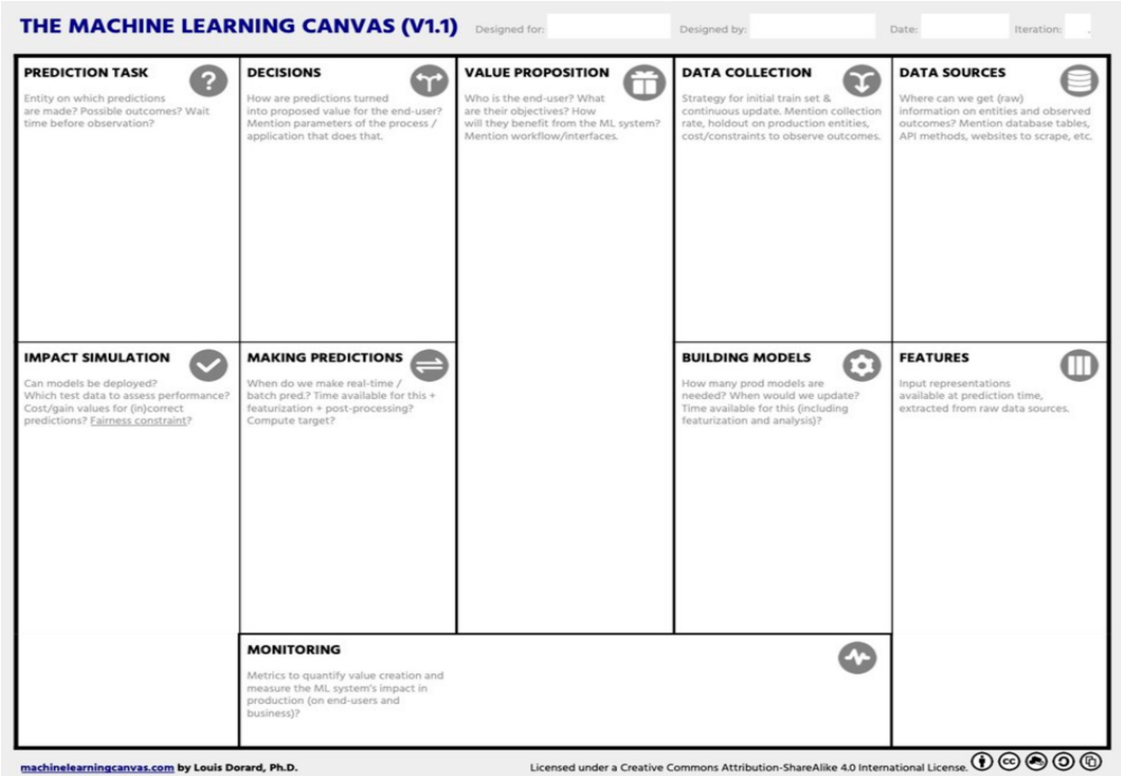


Figure 35. ML canvas (Donard, 2016).

In Figure 35, the central block highlights the value proposition of machine learning, outlining its objectives and the benefits it brings to end-users and stakeholders (Donard, 2016). On the right side of the *Value proposition*, data-related content illustrates how the machine learning system learns from data. Data sources demonstrate where data is sourced from. In previous sections, the significance of data collection was emphasized as a critical step in building ML algorithms and selecting models. On the right side of the ML canvas, *Data collection* is visualized and presented to stakeholders, providing clear insights into the methodologies to be implemented for data collection in the ML process. *Features* represent the input data; data scientists will analyze all variables to determine which features will be extracted. The model building block outlines the number of models required for the machine learning system, the frequency of updates, and the time needed for featurization and analysis. (Donard, 2016.)

On the left side of the *Value proposition*, *making predictions* draws from the learned data patterns, also known as a machine learning task. This phase presents the specific type of machine learning employed, along with the input and output parameters associated with the prediction process. Donard (2016) suggests deploying the different approaches for the classification task or defining and the regression task. This approach offers measurable metrics for assessing prediction accuracy. The *Decision* block establishes a precise objective for the machine learning task, aiming to deliver value to end-users and outlining how the goal will be accomplished. The *Impact Simulation* block evaluates the feasibility of the machine learning model, its associated costs, and the potential value it offers. *Prediction generation outlines the technical prerequisites and computing targets for the task and the expected duration.* The *Monitoring* block addresses metrics for quantifying value creation and assessing the machine learning's impact on end-users and business operations. (Donard, 2016.)

4.4 Conceptual framework

This section presents the conceptual framework of this thesis. The concept framework encompasses three parts demand forecasting, machine learning, and machine learning applied in the demand forecasting and supply planning as presented in Figure 36 below.

The first component in the conceptual framework is demand forecasting. First, it introduces demand forecasting, including its definition and significance. Then it proceeds to highlight the factors impacting demand forecasting and strategies to mitigate the *Bullwhip effects*. Lastly, it explores advanced methodologies in demand forecasting, focusing on machine learning techniques.

The second component is dedicated to Machine Learning. Its goal is to provide practical insights into selecting the appropriate ML model to address the challenges encountered by the case company. This component encompasses six key elements: ML definition, ML development, ML categories, ML algorithms, data preparation, ML build models, and model evaluation. It starts with fundamental concepts introduction, such as ML definition, development, and types. The goal is to offer a foundational understanding of ML. Additionally, the key roles are played by ML algorithms, data preparation, model building, and evaluation in order to present and analyze the specific machine learning algorithms recommended for the task. It includes significance of data preparation and techniques such as data cleaning, feature engineering, and data visualization. These steps are crucial to enabling the ML to efficiently discern patterns within the data and make accurate predictions. The final step involves training the model, validating its performance, and adjusting parameters to optimize its effectiveness.

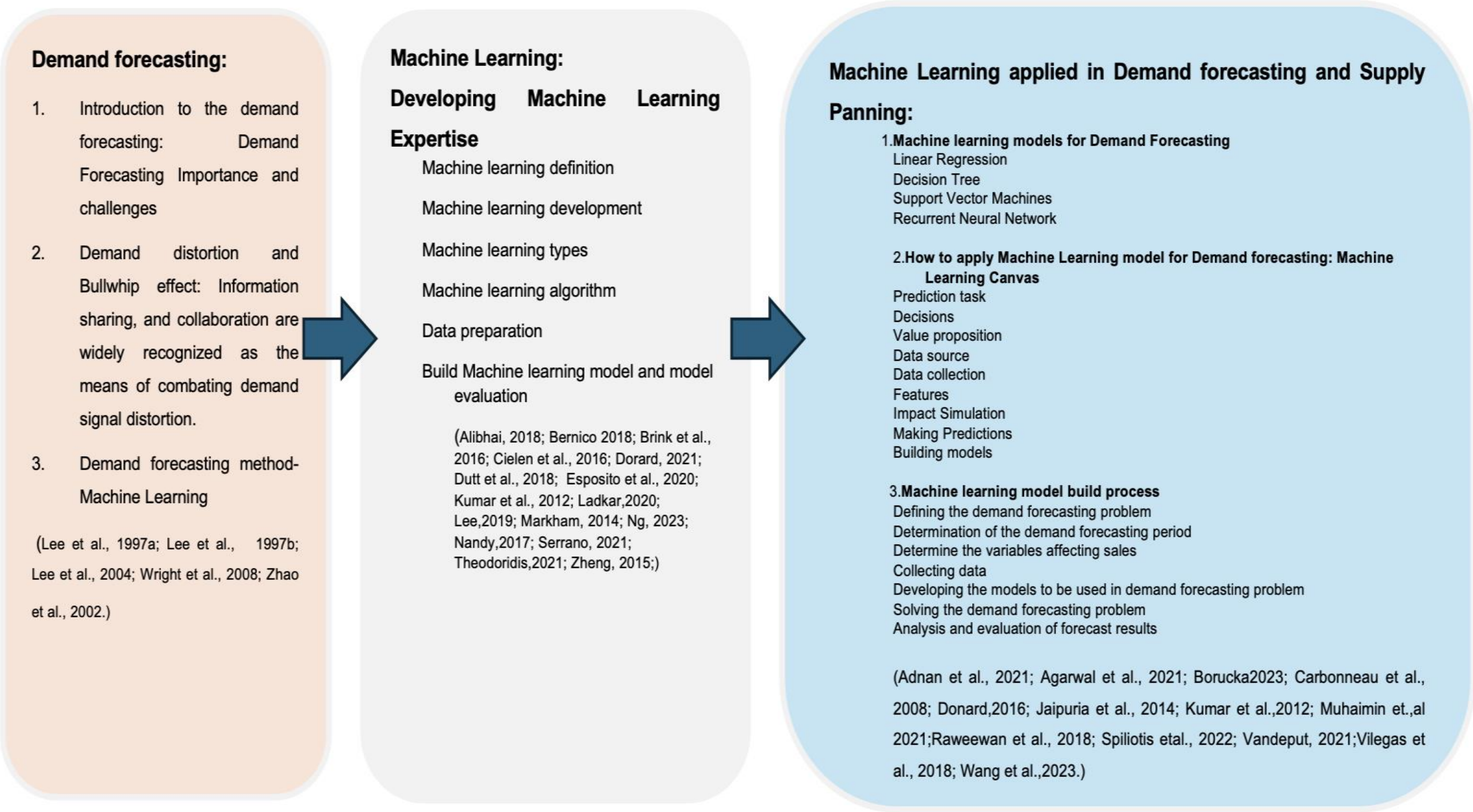


Figure 36. Conceptual framework for the proposal.

The third area of the conceptual framework delves into the application of ML in demand forecasting. Four ML models are employed for handling the demand forecasting task in the case company. Subsequently, it progresses to the process of constructing machine ML models, which entails seven steps aimed at providing insights and guidance for the task at hand. In addition, according to Donard (2016), the ML Canvas serves as a framework to establish links among data gathering, machine learning, and the generation of value. This phase also aims to visually represent all dimensions of machine learning to stakeholders. Lastly, the machine learning building process outlines each step and provides guidance for the demand forecasting in a real business context after the appropriate ML model is developed.

This current section presented industry specific knowledge to build the proposal. The next section will transit into the proposal development phase.

5 Building Proposal for Machine Learning Model for the Company

This section presents the steps to build an ML model to be used for demand forecasting and supply planning in the case company.

5.1 Overview of the Proposal Building Stage

As discussed in Section 3, the case company lacks a company-level demand forecasting tool. This leads to inaccurate forecasts and potential supply chain disruptions. In Section 4, an extensive review of literature and best practices was conducted to seek the best solution for this task. The feasible solution comes from ML and its application to demand forecasting and supply planning. According to the researchers' proposal in the field, ML emerges as a promising solution to complete the given task in this study (Zhao et al., 2002). The goal is to leverage ML techniques to mitigate the bullwhip effect and enhance demand accuracy (Lee et al., 1997a). The details of this section are presented as follows.

First, an internal meeting was conducted between the key stakeholders and the thesis researcher. During this meeting, the selected focus areas and relevant literature and best practice were discussed, and valuable suggestions for the proposal were gathered.

Second, ML Canvas was developed during the meeting. As shown earlier in this study, ML Canvas can serve as the guideline for building the ML model. During this phase, all variables and requirements that affected the model build were discussed in detail.

Third, an ML model for this given task was developed based on the finalized ML Canvas, integrating insights gathered from stakeholders and the relevant literature and best practice.

5.2 Findings from Data 2 (stakeholder inputs)

Finally, a draft proposal including three components: machine learning method for demand forecasting, machine learning demand forecasting process, and an integrated demand forecasting supply planning process were co-created with stakeholders and discussed again, for feedback and refinement. Table 8 below summarizes the key focus areas as well as suggestions from stakeholders.

Table 8. Stakeholders' inputs (Data 2) for the initial proposal building.

<table>
<tr><th></th><th>Key focus areas from CSA (from Data 1)</th><th>Inputs from literature (CF)</th><th>Suggestions from stakeholders for the Proposal, summary (from Data 2)</th><th>Descriptions of their suggestions (in detail)</th></tr>
<tr><td rowspan="2">1</td><td rowspan="2">Demand forecasting:
Inaccurate demand forecasting leads to excess stock and shortage.</td><td rowspan="2">Utilizing information sharing, collaboration, and advanced demand forecasting methods can enhance accuracy, mitigate the bullwhip effect, and optimize efficiency. (Lee et al., 2004)</td><td>"We've been solely relying on customers' orders. It's time to initiate demand forecasting to stabilize our supply Chain." (Order Fulfillment Specialist A.)</td><td>Order Fulfillment Specialist A at the Case Company proposed implementing demand forecasting prior to releasing purchase orders to suppliers.</td></tr>
<tr><td>"Implementing an improved forecasting system can help us minimize excess stock of components." (Sourcing Manager)</td><td>The Sourcing manager recommended integrating a demand forecasting process into the exiting supply and planning procedures.</td></tr>
<tr><td>2</td><td>Machine learning: The Case company lacks the demand forecasting method, solely relies on experts' experiences.</td><td>Machine learning won the top prize in the demand forecasting competition. It is demonstrated as an efficient method for predicting demands. (Vandeput et al., 2023)</td><td>"We lack experience with machine learning algorithms. Considering hiring dedicated data scientists for our operation team or collaborating with data scientists from the software department could be beneficial." (Operation Manager)</td><td>During the trial stage, the Operation Manager suggested to use data scientist from the software department.</td></tr>
<tr><td>3</td><td>Machine learning applied in demand forecasting</td><td>The commonly used ML models for demand forecasting include Linear Regression, Decision Tree, Recurrent Neural Network, and Support Vector Machine. The process of building a ML model proposes a practical approach for implementing models within a real business context. The ML Canvas offers guidelines and bridges the gap between data and stakeholders. (Vandeput et al., 2023; Donard 2016)</td><td>"Conducting a trial demand forecast using appropriate algorithms and our actual data would be advisable. Subsequently, we can compare the outcomes." (Data Scientists)</td><td>Data scientists requested all stakeholders to collaboratively discuss and enumerate elements outlined in the Machine Learning Canvas, encompassing factors influencing machine learning algorithms and model construction etc.</td></tr>
</table>

Table 8 highlights three primary focus areas: demand forecasting, ML, and machine learning applied in demand forecasting and supply planning. In each focus area, it provides a combination of academic solutions alongside stakeholder proposals.

First, inaccurate demand forecasting is a common challenge encountered by many companies. It can disrupt the supply chain, leading to excess stock and shortages. Researchers suggest that information sharing and collaboration among supply chain participants can alleviate this issue, resulting in stock reduction and supply optimization.

Moreover, according to Lee and other experts, the appropriate demand forecasting methods can mitigate this "*Bullwhip effect*" and enhance efficiency (Lee et al., 2004). Utilizing demand forecasting can stabilize the supply chain and reduce excess stock for the company. One internal stakeholder said in the brainstorming session as follows.

> "*We have been solely relying on customers' orders. It is time to initiate demand forecasting to stabilize our supply Chain." (Order Fulfillment Specialist A.)*

The second focus area is how to empower machine learning as a demand forecasting tool. Vandeput (2023) and other experts in demand forecasting highlight ML's efficiency in accurately predicting demand. ML can enhance supply chain visibility, optimize decision-making, and reduce costs for corporations (Vandeput 2023). Presently, the case company plans to use ML for demand forecasting but lacks the necessary expertise within its department. One solution is to request the data scientists from the software departments to collaborate on this task. An internal stakeholder from the case company offered his opinion in the brainstorming session as follows.

> "*We lack experience with machine learning algorithms. Considering hiring dedicated data scientists for our operation teams or collaborating with data scientists from the software department could be beneficial."* (Operation Manager.*)*

The third focus area involves the application of ML in demand forecasting. Four ML algorithms included *Linear Regression*, *Decision Tree*, *Recurrent Neural Networ*k, and *Support Vector Machine* are chosen for demand forecasting in this study. The ML Canvas, as highlighted by Vandeput et al. (2023) and Donard (2016), serves as a guideline bridging the gap between data and stakeholders. During the brainstorming session, data scientists urged all stakeholders to collaboratively discuss elements in the ML Canvas, including factors influencing ML algorithms and model construction. In the meeting, the data scientist proposed the following:

> *“Conducting a trial demand forecast using appropriate algorithms and our actual data would be advisable. Subsequently, we can compare the outcomes.”* (Data Scientist A.*)*

During the meeting, it was agreed that historical customer stock quantity as well as historical customer order quantity will be used as training data.

5.2.1 Development of The Case Company's ML Canvas

In this brainstorming session, a key focus is to discuss the ML canvas content which is guideline to build the ML model. Aligned with stakeholders, all essential elements are documented. The content presented in Figure 37 includes both requirements and variable factors influencing the model construction.

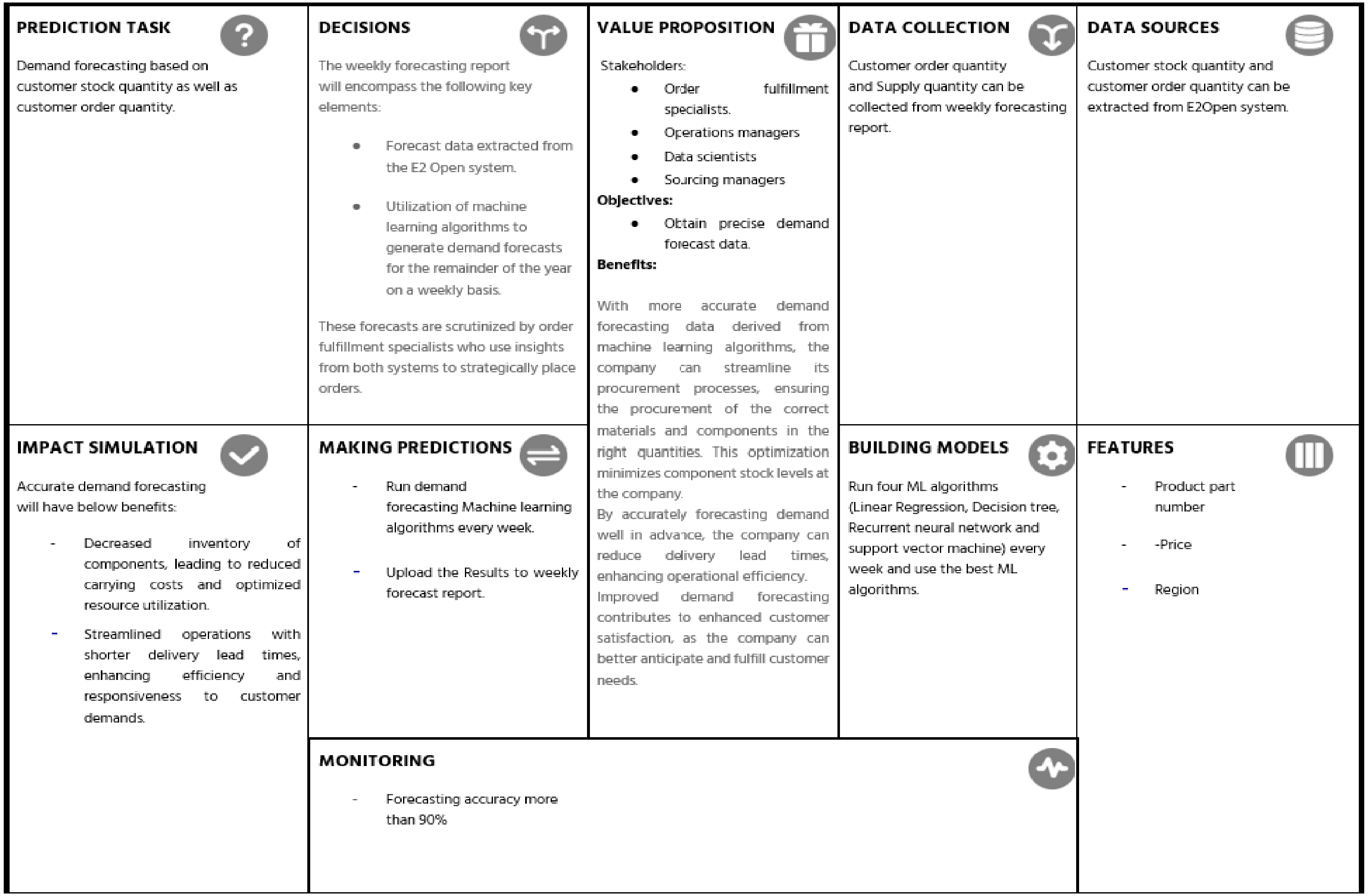


Figure 37. The case company´s ML canvas (edited by the thesis researcher).

In Figure 37, order fulfilment specialists, operation managers, data scientists, sourcing managers, and the author of this thesis participated in a brainstorming meeting. During this session, the requirements for machine learning development were aligned and documented within the ML canvas.

- Value proposition: The goal of this task is to achieve precise demand forecasts. By leveraging machine learning models to generate more accurate demand forecasts, the company can optimize its supply chain operations. This ensures the procurement of correct materials and components in the right quantities, minimizing stock levels and enhancing efficiency.

- Impact simulation: The stakeholders agreed in this meeting that accurate demand forecasting will yield the benefits shown as follows. Firstly, decreased inventory of components will lead to reduced costs and optimized resource utilization. Secondly, streamlined operations with shorter delivery lead time will enhance efficiency and responsiveness to customer demands.

- Decisions: The weekly commitment report serves as a significant data source for the current task, containing customer stock quantities, current customer order quantities etc., extracted from E2open system. Furthermore, it provides crucial insights for order fulfillment staff to place orders. Hence stakeholders decided to extract data from the commitment report weekly to train the dataset and develop the machine learning model.

- Prediction: The prediction task involves leveraging ML algorithms and models to forecast demand.

- Data collection and data sources: In this brainstorming session, stakeholders agree that data is extracted from the weekly commitment report. The data includes the supply quantity of the case company and the customer order quantity.

- Features: In this session, the data scientist proposed product number, price, and region are chosen as the features for the ML training.

- Building Model: During the ML building phase, four algorithms—*Linear Regression, Decision Tree, Recurrent Neural Network, and Support Vector Machine* will be employed to build models. It will run these analyses for three years of data and construct the most appropriate algorithm for the model. Evaluation will primarily rely on MAE and R-square metrics.

- Monitoring: ML evaluation metric, internal evaluation metric and stakeholder's feedback will be used to monitor the impact of this task.

Once the ML canvas was constructed, it progressed to the next phase: building the Demand Forecasting ML Model.

5.3 ML Demand Forecasting Model Building

Guided by the ML canvas, this section illustrates the ML model development process. In the proposal stage, the most appropriate ML algorithm and model were chosen for demand forecasting. It comprises a series of sequential steps:

1. Data collection
2. Data processing
3. Data visualization
4. Data feature engineering
5. Model training and testing
6. Model Evaluation
7. Model selection

Each of these will be illustrated in detail as follows.

5.3.1 Data collection and data processing

This section explains how the data was collected and prepared for building the ML model.

5.3.1.1 Data collection

The goal of this step was to review and analyze collected raw data, thoroughly clean the data for ML algorithm purpose. Before importing the data into the *Pandas library*, an initial processing step was undertaken to address primary elements, particularly incorrect values. For instance, mistakes such as missing history shipment data due to technical issues in the original database were corrected.

Since this thesis focuses on demand forecasting and supply planning, the primary goal was to forecast future customer stock quantity and customer order quantity based on historical data. The history shipment data was extracted from the order fulfillment database of the case company, spanning from January 2020 to December 2022. Customer stock quantity was linked to history shipment quantity from case company and customer order quantity is linked to demand forecasting.

Table 9 below presents one example of the data collected from January 3, 2022, to March 28, 2022, specifically for product 00NA from the case company. Monthly data from January to December were used for ordering materials and components in 2022, these data are not included in machine learning models build process.

Table 9. History data from 03 January 2022 to 28 March 2022 for product 00NA (internal document).

Date	Week	Customer Stock	Customer Orders	1	2	3	4	5	6	7	8	9	10	11	12
3/1/2022	1	1308	3259	913	0	930	2800	3657	2400	1200	1440	960	1500	1140	960
10/1/2022	2	3136	2666	0	0	1843	2800	3575	2200	1200	1440	960	1500	1140	960
01/17/2022	3	1585	3923	0	0	904	3739	3550	2200	1200	1440	960	1500	1140	960
01/24/2022	4	1435	3892	148	1	1113	3624	3516	2200	1200	1440	960	1500	1140	960
01/31/2022	5	1405	4169	0	1	5	3697	3490	2200	1200	1440	960	1500	1140	960
7/2/2022	6	1404	4285	0	1	423	3757	3470	2200	1200	1440	960	1500	1140	960
02/14/2022	7	1402	4685	0	1	423	3730	3364	2130	1139	1382	956	1500	1140	960
02/21/2022	8	1197	4720	0	332	797	3019	3364	2130	1139	1382	956	1500	1140	960
02/28/2022	9	188	3713	0	0	1258	3217	3364	2130	1139	1382	956	1500	1140	960
7/3/2022	10	182	4189	0	0	609	3129	3231	1600	1139	1382	956	1500	1140	960
03/14/2022	11	182	4601	0	0	0	3104	2980	1756	1139	1382	956	1500	1140	960
03/21/2022	12	226	4658	0	0	0	2335	2956	1780	1139	1382	956	1500	1140	960
03/28/2022	13	815	4766	0	0	0	2340	2443	2215	1139	1382	1004	1500	996	1020

As seen in Table 9, data scientists and stakeholders agreed to use Data, Week, Customer Stock, and customer orders information as training data. To be properly processed by machine learning algorithms, data scientists proposed to change the data and Week format into day/month/year. During the data collection and data clearing phase, certain weeks had entirely empty datasets, due to system maintenance by the end customer. Therefore, data for those entire weeks was deleted.

Table 10. History data from 25 January 2021 to 04 October 2021 for product 00A6.

Date	Week	Customer stock	customer orders	1	2	3	4	5	6	7	8	9	10	11	12
25/01/2021	4	133	789	88	134	967	147	226	184	230	276	184	275	274	200
01/02/2021	5	84	937	0	772	694	247	216	144	230	226	184	275	324	400
08/02/2021	6	59	1071	0	759	695	247	216	144	230	226	184	275	324	400
01/03/2021	9	41	1174	0	0	373	190	597	186	180	228	184	216	291	403
15/03/2021	11	32	1236	0	0	198	180	587	185	180	228	184	215	289	401
22/03/2021	12	31	1783	0	0	236	204	787	185	250	228	184	215	289	401
12/04/2021	15	206	1550	0	0	0	158	569	145	300	228	184	215	289	402
19/04/2021	16	991	1357	0	0	0	148	332	144	368	228	184	215	289	402
31/05/2021	22	342	1079	0	0	0	0	0	379	513	186	184	214	289	401
26/07/2021	30	324	1335	0	0	0	0	0	0	372	311	81	219	464	401
09/08/2021	32	682	2282	0	0	0	0	0	0	0	213	1069	220	632	871
16/08/2021	33	480	2144	0	0	0	0	0	0	0	0	944	124	522	641
23/08/2021	34	603	1889	0	0	0	0	0	0	0	0	944	124	522	641
30/08/2021	35	704	1969	0	0	0	0	0	0	0	0	974	124	679	644
06/09/2021	36	443	1927	0	0	0	0	0	0	0	0	1043	197	421	602
13/09/2021	37	336	1856	0	0	0	0	0	0	0	0	1151	22	79	84
20/09/2021	38	638	1376	0	0	0	0	0	0	0	0	40	294	317	106
27/09/2021	39	483	1113	0	0	0	0	0	0	0	0	0	300	268	106
04/10/2021	40	383	1025	0	0	0	0	0	0	0	0	0	138	256	91

In Table 10, data for Weeks 1, 2, 3, and 8 are absent due to holiday seasons at the start of January, where the system displayed zero customer stocks and orders. Consequently, data for these weeks was removed. Entries highlighted in red (e.g., 1069, 944) were found to be inaccuracies and were subsequently corrected data for these weeks was removed. Once all data was cleaned, it was exported to an Excel file and converted into a CSV format.

The next step involved importing the data into a Jupiter notebook which is one of the Python platforms. Figure 38 below shows the dataset summary.

```
import pandas as pd
data = pd.read_csv('00A6ALL.csv', delimiter=',')
print (data)
data.columns=['Date','Customer_stock','Customer_orders']
data.Date=data.Date.floordiv(100)
data.head(3)
```

```
           Date  Customer_stock  Customer_orders
0    17/02/2020             386               27
1    24/02/2020             399               35
2    02/03/2020             382              174
3    23/03/2020             132              247
4    01/04/2020             556             1544
..          ...             ...              ...
99    3/10/2022            1531             1903
100  10/10/2022            1530             1903
101  10/17/2022            1194              742
102  10/24/2022            1275             1052
103   7/11/2022             748              543

[104 rows x 3 columns]
```

Figure 38. Dataset Summary.

As seen in Figure 38, it includes 104 rows of data in total and 3 columns of data, which includes Date, Customer stock and customer orders information.

5.3.1.2 Data preprocessing

This thesis utilized several tools for its machine learning execution. Python was chosen as the primary programming language, with Jupiter Notebook serving as the platform for code writing and iteration. For data analysis, cleaning, exploration, and manipulation, the following libraries were employed: Pandas, NumPy, Matplotlib, Seaborn, and Scikit-learn. After all data is collected, the next phase is data visualization.

5.3.1.3 Data Visualization

Demand and supply trends from 2020 to 2022 were analyzed and visualized. The goal of data visualization is to visualize the trend and help build the right machine learning model. Figure 39 to Figure 41 are some examples of data visualization.

Figure 39 below shows visualization of demand and supply trend for product 00A6. The RED lines show customer stock trend, which is also the supply trend from the case company. The GREEN lines show the customer orders trend, which is the demand trend from the customer.

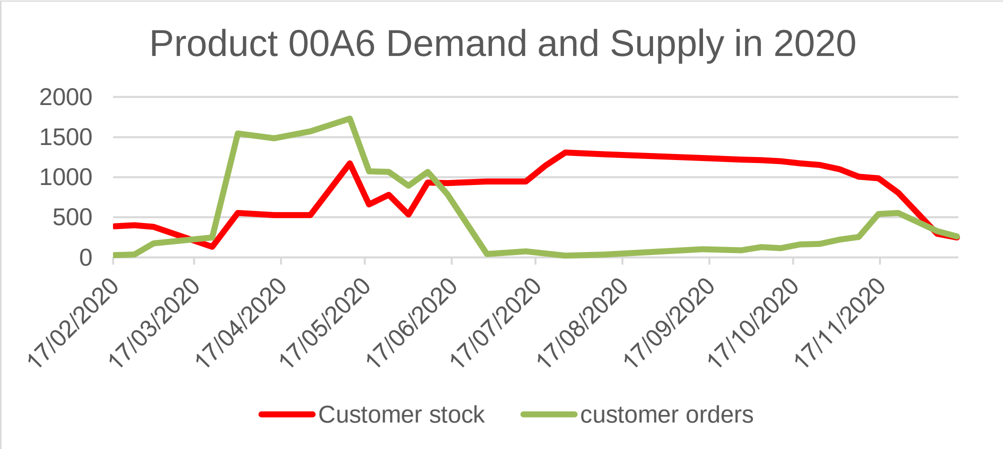


Figure 39. Product 00A6 Demand and Supply trend in 2020.

Figure 39 illustrates a pattern of low demand and customer stock at the beginning of the year. Demand begins to rise on 17.03.2020, consistently outpacing supply (customer stock) until around 17.06.2020. Afterward, supply consistently exceeds demand. By the end of 2020, demand nearly equals supply.

Figure 40 below shows Product 00NA demand and supply trend in 2020.

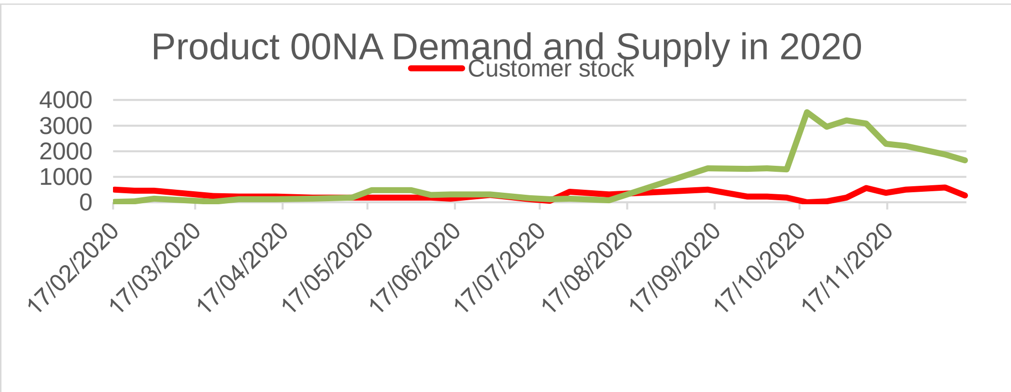


Figure 40. Product 00NA Demand and Supply trend in 2020.

As shown in Figure 40, there were low levels of both demand and supply from the start of the year until 17th August 2020. Subsequently, demand begins to rise, accompanied by an increase in supply. However, the increase in demand surpasses that of supply.

Figure 41 illustrates the demand and supply for product 00A6 in 2021.

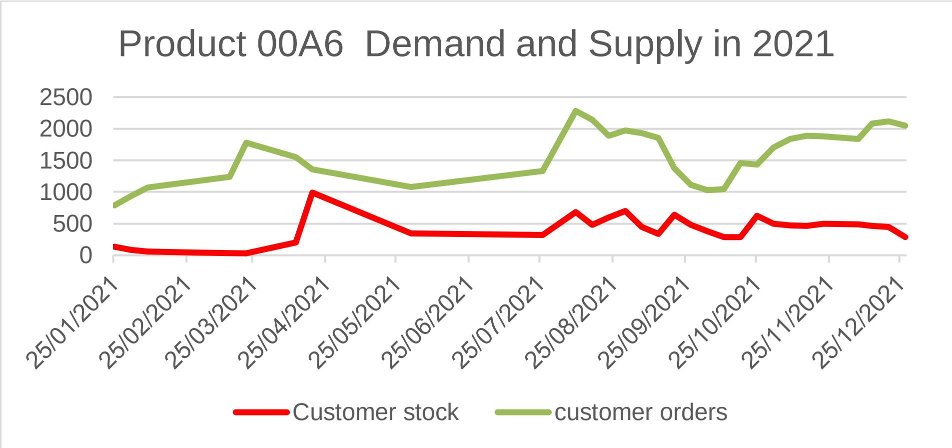


Figure 41. Product 00A6 Demand and Supply trend in 2021.

As shown in Figure 41, although demand remained consistently high throughout the year, the supply followed a similar trend but fell short of meeting demand requirements for the entire year.

After data visualization, it became apparent that supply consistently lags demand. Implementing an enhanced forecasting tool could help minimize this disparity. In the next section, it will examine and define ML feature engineering.

5.3.2 Feature Engineering

Feature engineering is crucial during the data processing phase. ML algorithms necessitate numerical inputs; Feature engineering is employed to transform categorical values into numerical representations. Product part numbers, price details, and sales regions were transformed into numerical formats, as shown in Table 11.

Table 11. Feature engineering for product part number, price, and sales region.

Product Part number	1= 00A6, 2=00NA
Price	1= price between 500 and 600USD, High price 2= price between 300-400 USD, low price
Sales Region	1= Europe, 2= Northern America

As seen from Table 11, product part number, price, sales region are key features of the data, and they are converted from categorical variables into numerical values.

5.3.3 Model Training and Testing

There are four ML models utilized for this training: *Linear Regression, Decision tree, Support Vector Machine and Recurrent Neural Networks* ML algorithms. After encoding features and formatting the data, the subsequent step involved creating training and testing datasets. Figure 42 presents the data splitting procedure.

```
# Splitting data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Figure 42. Data Split.

In Figure 42, an 80-20 split was adopted, with 80% of the data allocated for training and 20% for testing. To ensure randomness in the split, a random state of 42 was chosen, facilitating reproducibility. This approach enhances result replicability, allowing others to reproduce the ML algorithms effectively.

5.3.4 Model Evaluation

MAE is utilized as an appropriate metric for assessing the efficacy of an ML model. It quantifies the average absolute disparity between the actual and predicted values within the dataset. When Mean Absolute Error (MAE) equals 0, it indicates a perfect alignment between the predicted and actual values. (Zheng2015.)

R-squared(R^2) serves as a metric for assessing model fitness in ML, with values ranging from 0 to 1. A higher R-squared indicates better model fit. (Vandeput,2023.) In Figure 43 below, the mean absolute error approaches 0 and R-squared equals 1.0, indicating excellent performance of the linear regression machine learning algorithms.

5.3.4.1 Linear Regression

Figure 43 summarizes the results of MAE and Coefficient of Determination for Linear Regression.

```
   Year   W  Customer_stock  Customer_orders  Product  Price  Region
0  2020   7             386               27        1      1       1
1  2020   8             399               35        1      1       1
2  2020   9             382              174        1      1       1
3  2020  12             132              247        1      1       1
4  2020  14             556             1544        1      1       1
Mean Absolute Error: 9.68321030593997e-14
Coefficient of Determination (R^2): 1.0
```

Figure 43. Mean Absolute Error and R squared for Linear Regression.

As shown in Figure 43, the MAE for Linear Regression is 9.68×10^{-14}. The result is close to zero. R2 is equal to 1.

Residuals represent the variance between actual and predicted values. It is illustrated in Figure 44 below. When actual values match predicted values, the residual equals 0.

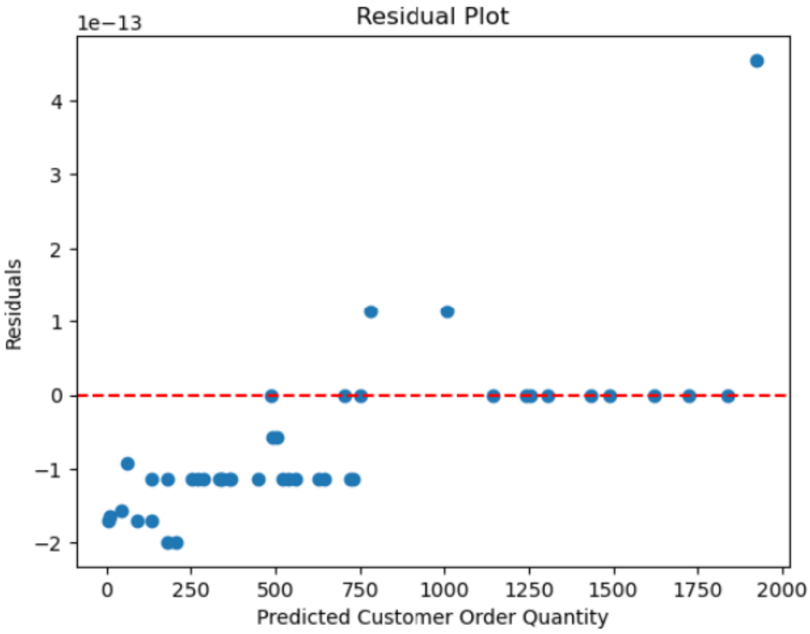


Figure 44. Residual plot for Linear Regression.

Figure 44 indicates numerous residuals equal to 0, signifying identical predicted and actual values. However, some residuals deviate from 0, indicating disparities between predicted and actual values.

Figure 45 shows the distribution of residuals for Linear Regression.

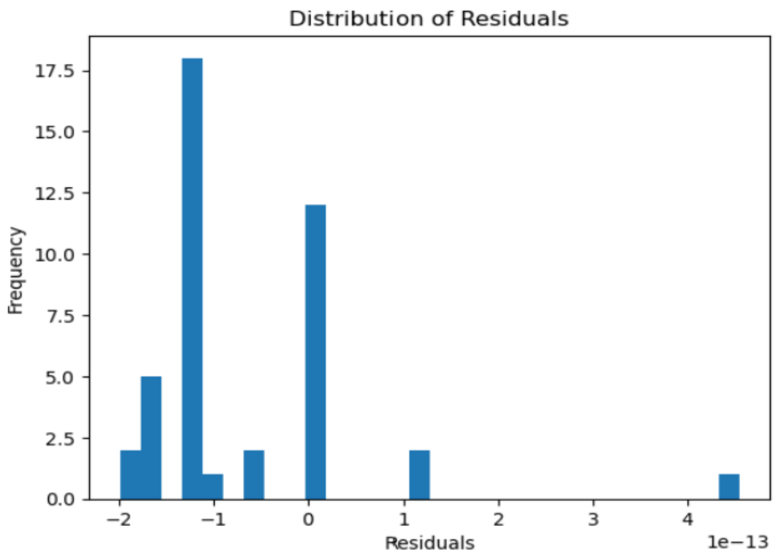


Figure 45. Distribution of Residuals.

Figure 45 displays the Residuals' distribution. A normal distribution of Residuals implies a well-fitted linear regression model.

5.3.4.2 Decision Tree

Figure 46 below shows the MAE and Coefficient of Determination for Decision tree.

```
   Year   W  Customer_stock  Customer_orders  Product  Price  Region
0  2020   7             386               27        1      1       1
1  2020   8             399               35        1      1       1
2  2020   9             382              174        1      1       1
3  2020  12             132              247        1      1       1
4  2020  14             556             1544        1      1       1
Mean Absolute Error: 7.3023255813953485
Coefficient of Determination (R^2): 0.9994821345466534
```

Figure 46. Mean Absolute Error and R squared for Decision Tree.

As seen in Figure 46, MAE equals 7.3, Coefficient of Determination is 0.99, remarkably close to 1.

Figure 47 below shows the Residual plot for Decision tree.

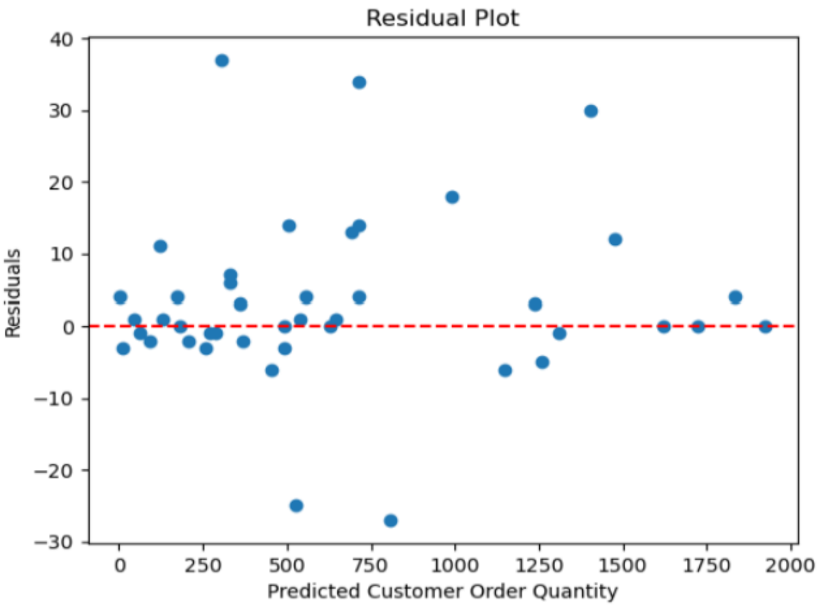


Figure 47. Residual plot for Decision Tree.

As seen in Figure 47, few of the Residuals are equal to zero, many of them are scattered everywhere.

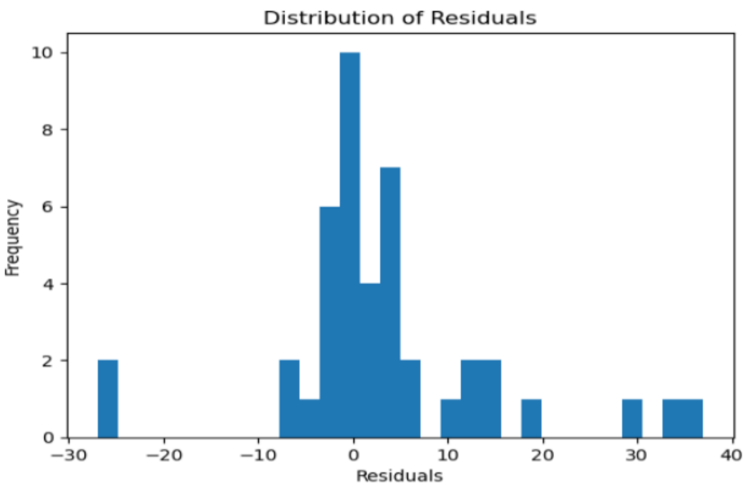


Figure 48. Distribution of Residuals for Decision Tree.

As shown in Figure 48, it shows that the residual is distributed around 0, few are distributed far away from 0. It also shows that the distribution of Residuals is normal distribution.

5.3.4.3 Support Vector Machine

Figure 49 below shows the MAE and Coefficient of Determination for Support Vector Machine.

```
   Year   W  Customer_stock  Customer_orders  Product  Price  Region
0  2020   7             386               27        1      1       1
1  2020   8             399               35        1      1       1
2  2020   9             382              174        1      1       1
3  2020  12             132              247        1      1       1
4  2020  14             556             1544        1      1       1
Mean Absolute Error: 418.9440928353246
Coefficient of Determination (R^2): -0.20857074987151947
```

Figure 49. Mean Absolute Error and R squared for Support Vector Machine.

As seen in Figure 49, MAE is around 418, much larger than 1, but coefficient of Determination is even smaller than zero.

Figure 50 shows the Residual plot for Support Vector Machine, most of them are far away from Zero.

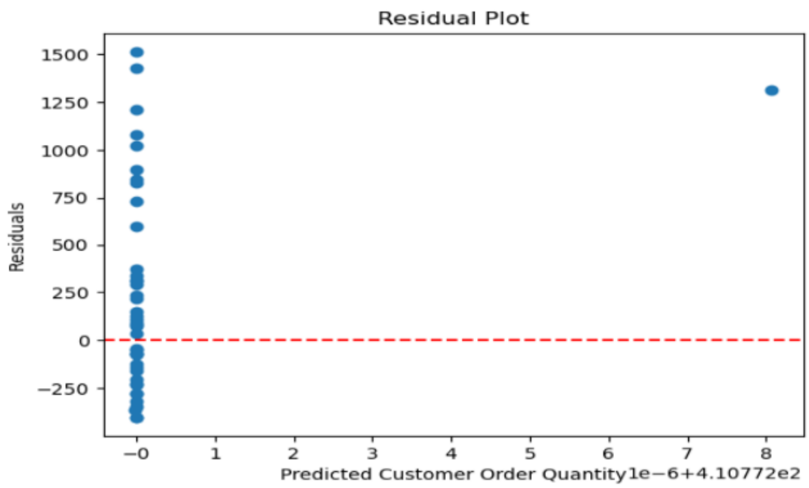


Figure 50. Residual plot for Support Vector Machine.

Figure 51 below shows the distribution of Residuals for Support Vector Machine, as shown in Figure, the distribution is not normal distribution.

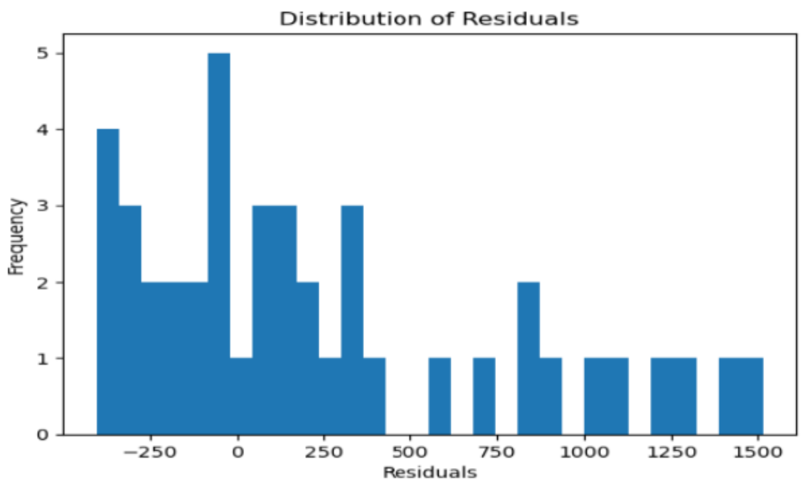


Figure 51. Distribution of Residuals for Support Vector Machine.

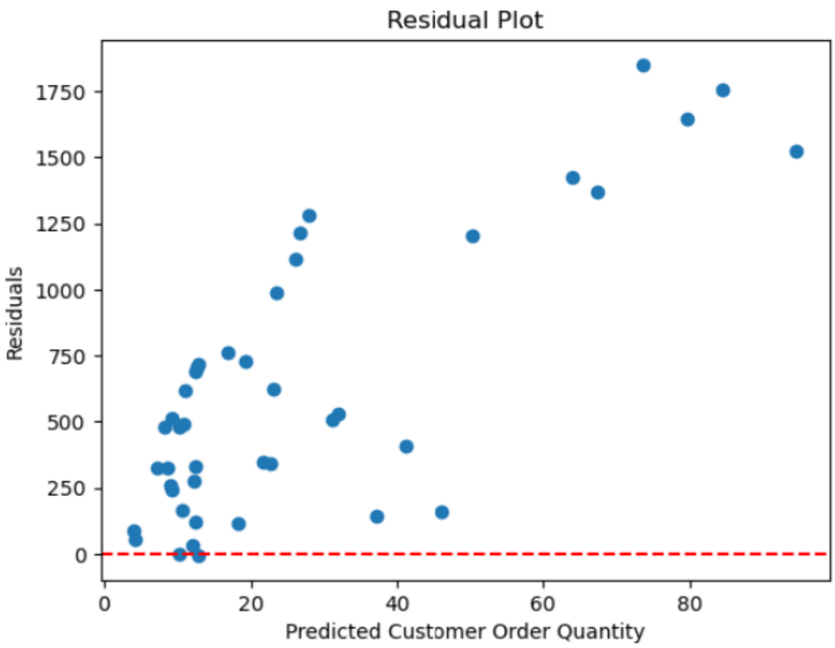
5.3.4.4 Recurrent Neural Network

Figure 52 shows the MAE and R squared for Recurrent Neural Network, MAE is around 653866, much bigger than 1. Coefficient of Determination is also smaller than Zero.

```
Mean Squared Error: 653866.590285341
Coefficient of Determination (R^2): -1.3274362984133599
```

Figure 52. Mean Absolute Error and R squared for Recurrent Neural Network.

Figure 53 shows the Residual Plot for Recurrent Neural Network, only few of the Residual is zero, many of the Residuals are much larger than zero.



.

Figure 53. Residual plot for Recurrent Neural Network.

Figure 54 below shows the residuals distribution for Recurrent Neural Network.

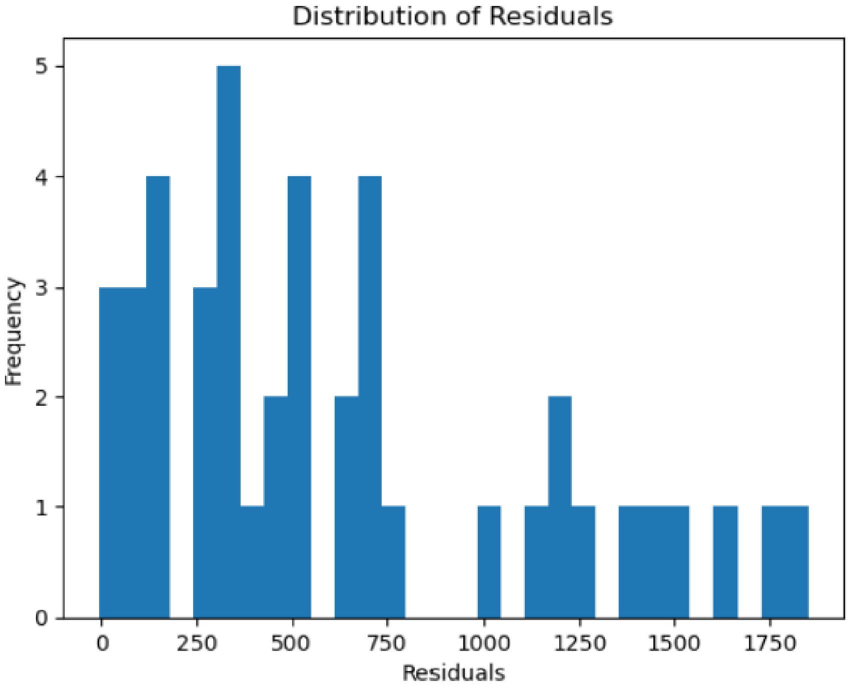


Figure 54. Residuals distribution for Recurrent Neural Network

As shown in Figure 54, the distribution is not normal distribution.

5.3.5 Model Selection

Table 12 shows the evaluation results for four ML models, assessed using two metrics: MAE and Coefficient of Determination. The models include *Linear Regression, Decision Tree, Support Vector Machine, and Recurrent Neural Network.*

Table 12. MAE and R2 validation for four Machine Learning Algorithm.

ML Algorithms	Mean Absolute Error (MAE)	Coefficient of Determination(R^2)
Linear Regression	9.68E-14	1
Decision Tree	7.3	0.99
Support Vector Machine	418.94	-0.20
Recurrent Neural Network	653866	-1.32

In Table 12, Coefficient of Determination for Linear Regression is 1, and that of Decision Tree is 0.99, but the Mean Absolute Error for Linear Regression is much smaller than that of Decision Tree. Linear Regression is with the smallest MAE and the highest R^2.

According to Dutt et al., (2018), “MAE and R-squared are known as the valuable metric for assessing model fitness. A lower MAE and higher R-squared value indicates a better fit.” (Dutt et al., 2018, Chapter 3.)

5.4 Initial Proposal

After constructing the initial ML model for demand forecasting, the team evaluated various models. The evaluation results demonstrated that the linear regression model best suited the task. A stakeholder meeting was then conducted to discuss their expectations and how to implement the ML model into the demand forecasting process. Attendees included Data Scientists from the software department, Order Fulfilment Specialists, the Sourcing Manager, the Operations Manager, and the VP of the Operation. The initial proposal includes three main components as follows.

1. Presenting the developed ML model.

2. Mapping out and presenting the ML model development process to stakeholders.

3. Integrating the ML model into the initial demand forecasting and supply planning process.

Since ML model has been illustrated through its build process, the other two will be explained as follows.

Firstly, an ML model development process was mapped out, showing as Figure 55 below. It illustrates the entire process of demand forecasting by using ML algorithms. This sub process of demand forecasting by machine learning is part of the updated Demand and Supply Planning Process, highlighted in Figure 56.

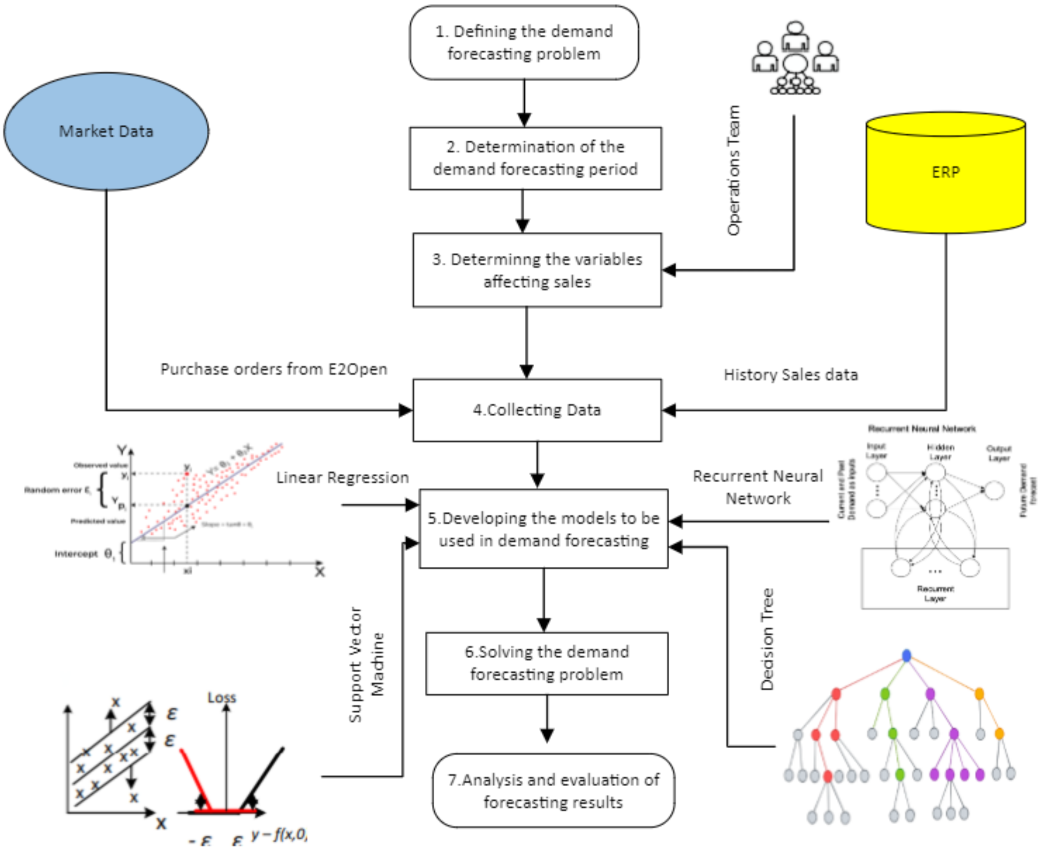


Figure 55. Sub Process of demand forecasting by Machine Learning.

Figure 55 illustrates the detailed process of demand forecasting through machine learning. The first step is to define the demand forecasting problem. In this case, future demand needs to be estimated based on historical sales data as well as current customer orders. The second step involves determining the demand forecasting period. The case company aims to obtain demand forecasts for the next three to six months. Thirdly, it is essential to identify the variables affecting sales. For the case company, two variables influence sales: price and region. It is evident that lower prices lead to higher sales, and there is greater demand in the US compared to Europe for products from the case company. The next step is data collection, which requires two sets of data for demand forecasting through machine learning: historical sales data from the ERP system and purchase order quantities from the Market database. Following data collection, four ML models will be tested, including Linear Regression, Support Vector Machine, Recurrent Neural Networks, and Decision Trees. Following that, the results from these ML models will be evaluated, and the most effective model will be selected based on the findings.

Secondly, during the meeting, stakeholders also reviewed and refined the Demand and Supply Process. Figure 56 illustrates the updated process, with newly added processes highlighted in green. This includes the subprocess of demand forecasting by ML, as well as analyzing the demand and supply trends and adjusting the supply accordingly.

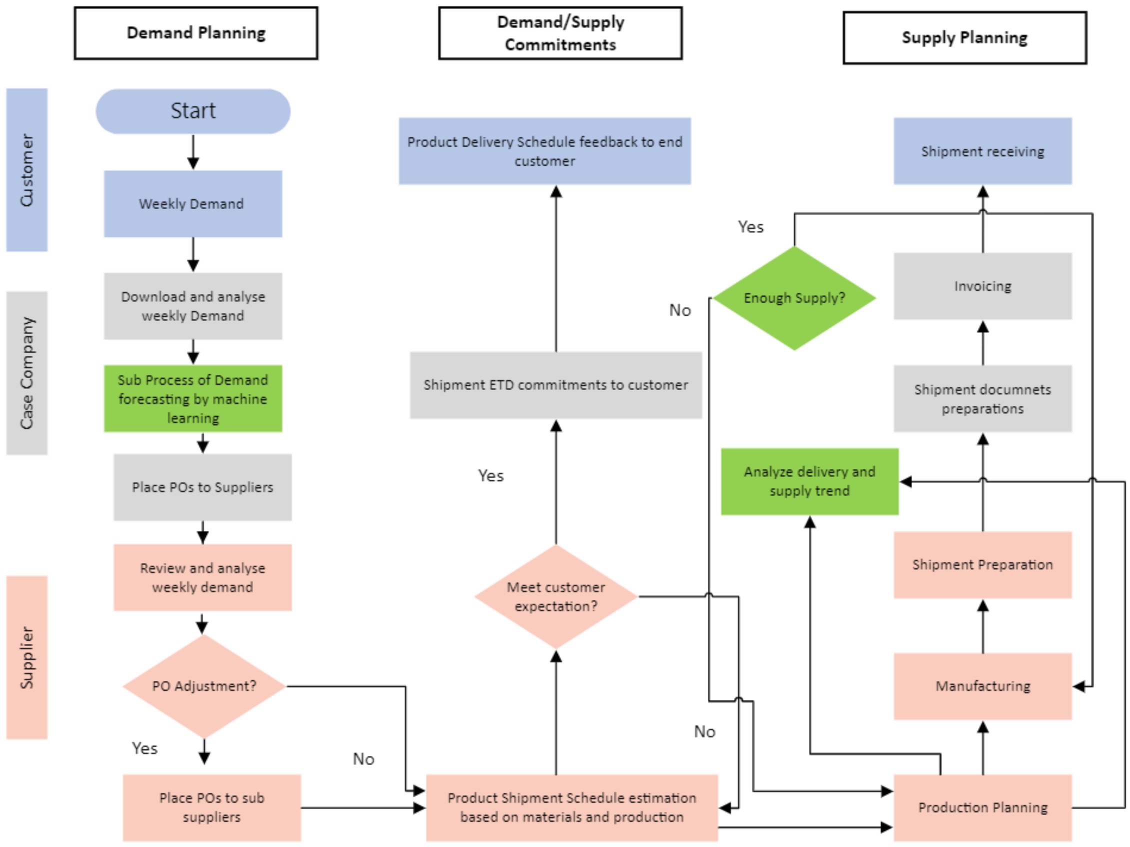


Figure 56. Updated Demand Forecasting and Supply Planning Process.

In Figure 56, three stakeholders are involved in the updated demand and supply planning process: the customer, the case company, and the supplier, each marked with distinct colors in the process. The demand and supply planning process comprises three sub-areas: Demand Planning, Supply Planning, and Demand-Supply Commitments.

The customer updates weekly demand in the E2Open system. The case company downloads and analyzes the demand from the E2Open system. After obtaining the weekly demand information from the E2Open system, it was proposed to utilize the ML model to make forecasts before placing purchase orders to the suppliers. The ML results will be compared with the forecast baseline to assist order fulfillment in making better decisions. The subprocess of demand forecasting by machine learning has been explained in Figure 55.

After receiving the purchase orders (POs) from the case company, the supplier will document it in the ERP system, indicating critical-to-build (CTB) shortage materials. The supplier then places POs to its sub-suppliers. Sub-suppliers estimate component delivery dates, and the supplier collects all component delivery dates to provide an estimated product delivery date to the case company. The case company reviews the estimated product delivery data to ensure it meets customer demand. If it does, they commit to product delivery in the E2Open system; if not, the case company investigates how to improve the delivery schedule and shorten the lead time. Various measures, such as purchasing components from the spot market, can be taken to shorten the lead time. Once commitments are received from the case company, the end customer receives the estimated delivery date directly from the E2Open system.

When the production plan is released, it is proposed that the case company checks and compares the demand trend with the supply trend to ensure better alignment between supply and the demand forecasted by machine learning. The company analyzes supply and demand trends upon receiving production plans. If demand exceeds supply, discussions with suppliers are initiated to increase production; conversely, oversupply prompts supply reduction.

Once the production plan is confirmed by the case company, the supplier begins manufacturing the products and arranges shipments post-production. The case company provides shipping documents and invoices to the customer upon completion of shipment.

This section outlines the step-by-step formation of the initial proposal. The following section will transit into the evaluation and development phase, leading to the final proposal.

6 Validation of the Proposal

This section presents the findings from the validation phase and highlights additional advancements to the initial proposal. In the end, the final proposal and action plan are introduced.

6.1 Overview of the Validation Stage

This stage presents the validation results of the proposal developed in Section 5, comprising four stages. First, validating the ML model via ML evaluation metrics; second, validating the ML model using internal evaluation metrics. Third, integrating the ML model into the initial demand forecasting and supply planning process, and collecting stakeholder feedback. Finally, presenting the new integrated demand forecasting and supply planning process map to stakeholders and displaying the implemented plan.

6.1.1 ML metric Validation

Firstly, the ML model was validated using the MAE and R^2 evaluation metrics introduced by data scientist Ladkar (2020). Based on the ML evaluation metrics, achieving the lowest MAE and highest R^2 values indicates that this model is most appropriate for the given task. The evaluation metric was also discussed in the previous literature review and during the model building phase. To aid understanding, the MAE and R^2 evaluation results were presented again as shown in Table 13.

Table 13. MAE and R2 Evaluation Results.

ML Algorithms	Mean Absolute Error (MAE)	Coefficient of Determination(R2)
Linear Regression	9.68E-14	1
Decision Tree	7.3	0.99
Support Vector Machine	418.94	-0.20
Recurrent Neural Network	653866	-1.32

In Table 13, the MAE and R^2 scores for each model are presented as follows: Linear Regression achieved a MAE score of 9.68E-14 and an R^2 score of 1; Decision Tree attained a MAE score of 7.3 and an R^2 score of 0.99; Support Vector Machine yielded a

MAE score of 418.94 and an R^2 score of -0.20; Recurrent Neural Network obtained a MAE score of 653866 and an R^2 score of -1.32. Among these, the Linear Regression model demonstrated that it is the most appropriate one for this given task.

6.1.2 Internal Validation

The most appropriate machine learning model was also validated through the case company internal evaluation metrics as required in the ML Canvas. Figure 59 below shows summary of demand forecasting by using linear regression for two products, 00A6 and 00NA, for the calendar year of 2023. The historical training data is based on data from 2020 to 2022. Actual sales quantities for two products, 00A6 and 00NA for the whole year of 2023 were also presented. Accuracy was calculated based on the forecasted quantity as well as for the actual sales quantity during the same period.

	Date	Product	Actual Sales Quantity(PCS)	Accuracy
0	Q1 2023	00A6	16605	N.A
1	Q1 2023	00NA	52233	N.A
2	Q2 2023	00A6	28332	N.A
3	Q2 2023	00NA	48964	N.A
4	Q3 2023	00A6	28855	N.A
5	Q3 2023	00NA	42603	N.A
6	Q4 2023	00A6	19782	N.A
7	Q4 2023	00NA	33327	N.A
8	Date	Product	Demand Forecast by Machine Learning(PCS)	Accuracy
9	Q1 2023	00A6	15467	0.931466426
10	Q1 2023	00NA	53498	0.975781594
11	Q2 2023	00A6	27456	0.969080898
12	Q2 2023	00NA	47069	0.961298097
13	Q3 2023	00A6	30056	0.958378097
14	Q3 2023	00NA	44787	0.948736005
15	Q4 2023	00A6	21009	0.937973916
16	Q4 2023	00NA	34559	0.963032976

Figure 57. Demand forecasting results and actual sales quantity for 2023.

As shown in Figure 57, forecasting accuracy for the whole year 2023 is more than 90%, with highest accuracy around 97% and lowest accuracy around 93%. The stakeholders required the prediction accuracy should be more than 90%. The Linear Regression Model demonstrated that it could meet the requirements.

6.2 Developments to the Initial Proposal (based on Data Collection 3)

Since Linear Regression was validated as the most suitable for the task, this phase shifted focus to refining the initial proposal—the integration of the ML model into the existing demand forecasting and supply planning process. Before finalizing the proposal, a meeting took place between the relevant stakeholders and the author of this thesis. The purpose of the meeting was to collect feedback on the initial proposal. Key focus areas, existing knowledge, initial feedback, and the most recent feedback were documented in Table 14.

Table 14. Expert suggestions (findings of Data 3) for the Final proposal.

	*Key focus areas from **CSA** (from **Data 1**)*	*Inputs from literature (**CF**)*	*Suggestions from stakeholders for the Proposal, summary (from **Data 2**)*	*Descriptions of their suggestions (in detail)*	*Development **(Data 3**)*
1	Demand forecasting: Inaccurate demand forecasting leads to excess stock and customer delivery shortage.	Utilizing information sharing, collaboration, and advanced demand forecasting methods can enhance accuracy, mitigate the bullwhip effect, and optimize efficiency. (Lee et al.,2004)	"*We've been solely relying on customers' orders. It's time to initiate demand forecasting to stabilize our supply Chain.*" (Order Fulfillment Specialist A.)	Order Fulfillment Specialist A proposed implementing demand forecasting prior to releasing purchase orders to suppliers.	"*Machine learning models only work for products that have historical data, not applicable for new products. For new products, it would be better to get customer order quantities directly from the marketing department.*" (Operation Manager)
			"*Implementing an improved forecasting system can help us minimize excess stock of components.*" (Sourcing Specialist)	The Sourcing Specialist recommended integrating a demand forecasting process into the exiting supply and planning procedures.	"*New roles and responsibilities should be defined and added to our process, since Machine learning has been included.*" (Sourcing Manager)

2	Machine learning: The Case company lacks the demand forecasting method, solely relies on experts' experiences.	Machine learning won the top prize in the demand forecasting competition. It is demonstrated as an efficient method for predicting demands. (Vandeput et al., 2023)	"*We lack experience with machine learning algorithms. Considering hiring dedicated data scientists for our operation teams or collaborating with data scientists from the software department could be beneficial." (Order Fulfillment Manager*)	The Order Fulfillment Manager requested the software department's data scientists, well-versed in machine learning algorithms, to collaborate.	"*We made demand forecasting only for two products so far, we should make demand forecasting for all our products.*" (Operation manager) "*In the future, we need to hire data analysts to our operation team for machine learning demand forecasting tasks because we have a lot of products to be analyzed*" (VP of Operation)
3	Machine learning applied in demand forecasting	The Machine learning Canvas offers guidelines and bridges the gap between data and stakeholders. (Vandeput et al., 2023; Donard 2016)	*"Conducting a trial demand forecast using appropriate algorithms and our actual data would be advisable. Subsequently, we can compare the outcomes." (Order Fulfillment specialist B.)*	Data analyst requested all stakeholders to collaboratively discuss and enumerate elements outlined in the Machine Learning Canvas, encompassing factors influencing machine learning algorithms and model construction etc.	"*We should always check and follow the accuracy by machine learning demand forecasting, the accuracy target is min 90%.*" (Conclusions from all the stakeholders)

Firstly, Table 14 highlights the significance of demand forecasting with appropriate methods as the primary focus area. A consensus was reached that ML-based demand forecasting should be prior to the release of PO to suppliers. The operation manager commented as follows.

> "*Machine learning models only work for products that have historical data, not applicable for new products. For new products, it would be better to get customer order quantities directly from the marketing department.*"

All stakeholders agreed that ML demand forecasting is applicable solely to products with historical sales data. For new products without such data, the case company should use alternative methods, such as forecasting based on customer orders.

Secondly, upon implementation of the ML model, there will be slight adjustments to roles and responsibilities within the relevant department. The sourcing manager emphasized the importance of clearly defining these changes, especially regarding the involvement of the data analyst. His comment was presented as follows.

> *“New roles and responsibilities should be defined and added to our process, since Machine learning algorithms and models haven been included.” (Sourcing Manager)*

Thirdly, the focus shifts to ML methods application. During the initial trials, ML model was conducted on only two products, 00A6 and 00NA. With over one hundred products in the case company, the operations manager proposed extending machine learning demand forecasting to cover all products. He had the comments as follows.

> “*We made demand forecasting only for two products so far, we should make demand forecasting for all our products.*” (Operation manager)

The VP of Operations proposed that hiring a data scientist for the operations team would be necessary. The new data scientist can handle the workload associated with machine learning demand forecasting tasks in the future. His proposal was presented below.

> “*In the future, we need to hire data scientist to our operation team for machine learning demand forecasting tasks because we have a lot of products to be analyzed*” (VP of Operation)

Finally, the initial demand forecasting and supply planning map should be seamlessly integrated and updated with the newly introduced elements.

In summary, the validation stage comprised three components outlined below.

	Initial Proposal Category	ML Evaluation Metric	Intenal Evaluation Metric	Stakeholder Feedback
1	**ML Model Validation (Linear Regression)**	Linear Regression emerges as the model scoring the smallest MAE and the highest R2.	Linear Regression demonstrated that forecasting accuracy for the whole year 2023 is more than 90%, with highest accuracy around 97% and lowest accuracy around 93%.	Suggested the ML model can be applied for all current products. Currently it is applied for two products.
2	**ML Process for Demand Forecasting**	Validated through Stakeholder Feedback	Validated through Stakeholder Feedback	For optimal performance, the Linear Regression Model is recommended, thus other models should be excluded. Documentation should confirm an accuracy exceeding 90%. If the outcome falls short, retraining the model is necessary
3	**Integrated Demand Forecasting and Supply Planning Process**	Validated through Stakeholder Feedback	Validated through Stakeholder Feedback	Machine learning models are ideal for products with historical demand data. However, for new products, an alternative approach should be employed.

Figure 58. Validation State

As presented in Figure 58, during the validation phase, the Linear Regression model emerged as the most suitable ML model for this assigned task. It displayed impressive performance across both ML and internal evaluation metrics. Therefore, stakeholders recommended the implementation of this ML model across all current products within the case company.

Moreover, stakeholders proposed to exclude other ML models from the process map and keep the inclusion of only the Linear Regression model in the process map. Furthermore, it was advised that the process map should document an accuracy surpassing 90% according to internal evaluation metrics.

In terms of the integrated demand forecasting and supply planning process, stakeholders suggested incorporating a phase in which ML models are applied to current products with historical data for demand forecasting. However, for new products lacking historical data, demand forecasts will rely on customers' orders.

The next section will transit to the final proposal.

6.3 Final Proposal

This section presents the final proposal. It entails three important elements: a suitable machine learning model for demand forecasting, a machine learning process for demand forecasting and an integrated machine learning applied in the demand forecasting and supply planning process.

Firstly, following validation, as discussed earlier linear regression has the lowest MAE and best Coefficient of Determination(R^2) values compared to other ML algorithms. The final proposal is to use linear regression ML algorithm to make demand forecasting. Since the Linear regression ML model has been concretely discussed and passed two evaluation metrics, the following section will focus on the other two elements.

Secondly, as per all stakeholders' feedback and recommendation, the initial ML demand forecasting process was updated with necessary improvement. The final proposal of ML demand forecasting process is presented as follows.

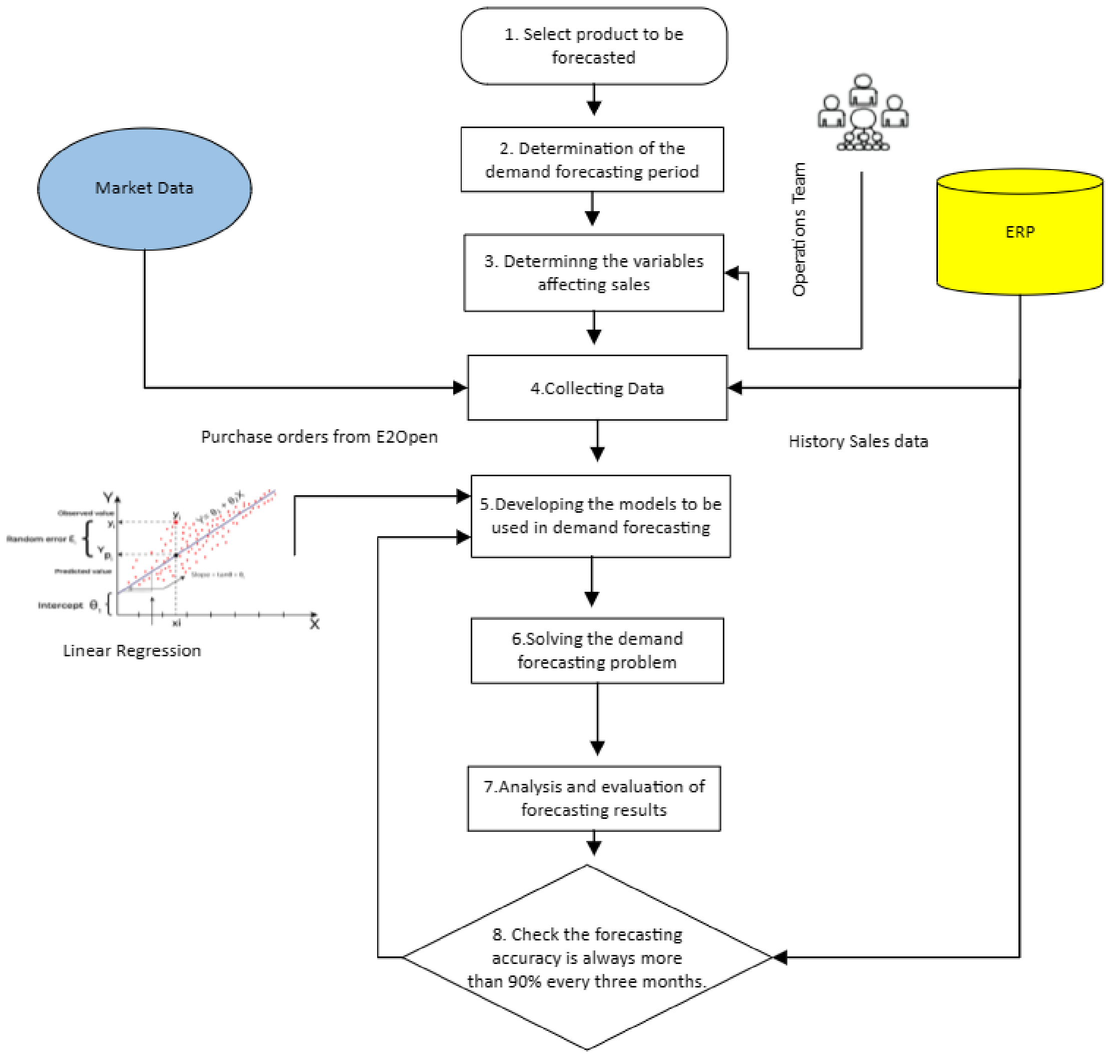


Figure 59. Final Proposal of machine learning demand forecasting process.

As presented in Figure 59, the first step is to select the products to be forecasted. Stakeholders proposed conducting demand forecasting for all products with historical sales data. The second step involves determining the demand forecasting period. It was discussed and agreed with stakeholders that the forecasting period would encompass the remaining months of the year. Thirdly, it is essential to identify the variables that affect sales and forecasting data. As explained in the previous section, for products from the case company, product price and sales regions are the main variables impacting sales. Next, historical sales data for the forecasted products needs to be collected. Following data collection, data analysts can commence developing Linear Regression forecasting models and initiating demand forecasting. Once the demand forecasting results are available, data scientists need to check for errors in the forecasted data and clean the data when necessary. Finally, stakeholders have agreed to assess forecasting accuracy every three months, ensuring it exceeds 90%. Forecasting accuracy can be verified by comparing the forecasting data with actual sales quantities for the same time. Finally, stakeholders are committed to assessing forecasting accuracy every three months, ensuring it surpasses 90%. This involves comparing forecasted data with actual sales quantities for the same period.

Thirdly, the final proposal of demand and Supply planning process, integrated with machine learning demand forecasting is presented as follows.

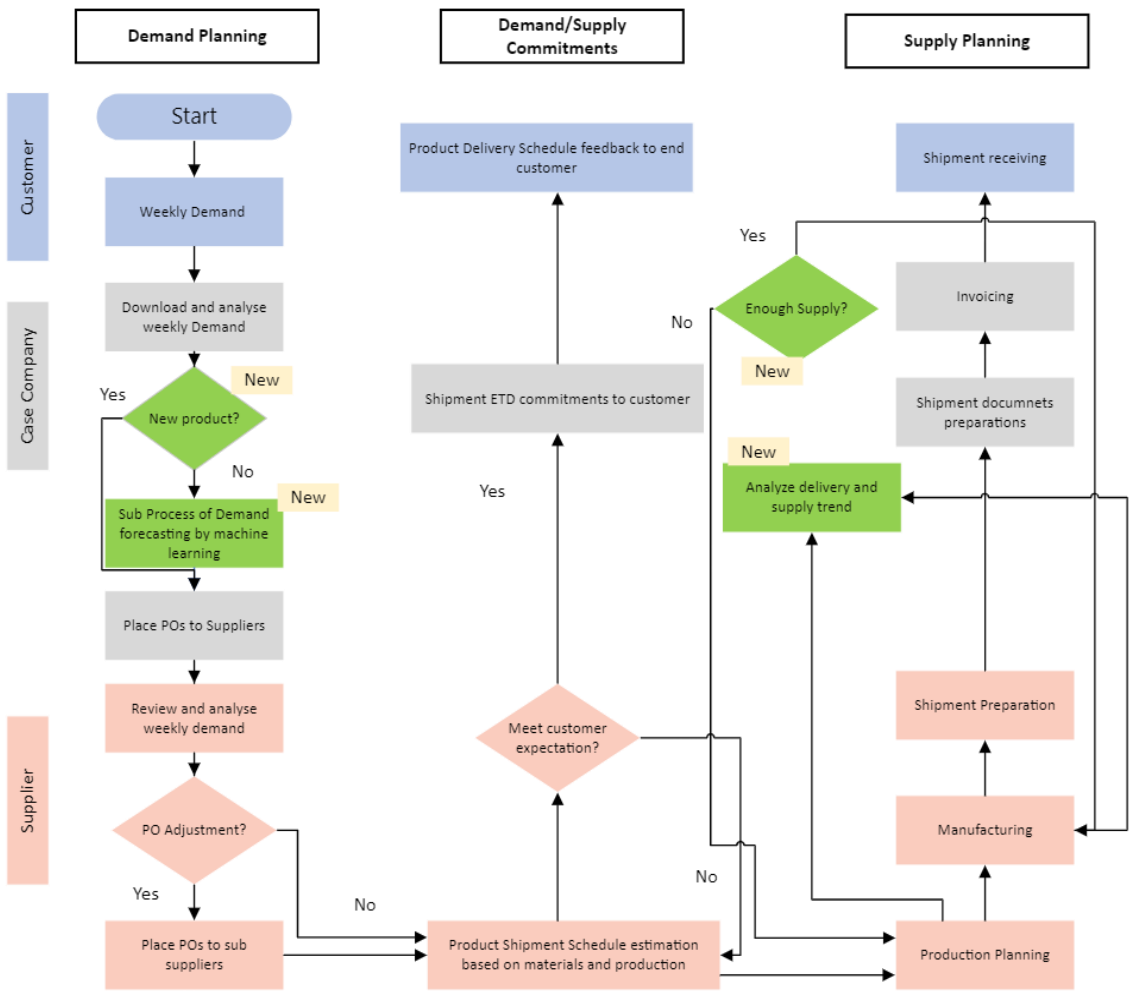


Figure 60. Final proposal of Demand and Supply Planning Process.

In Figure 60, new processes are highlighted in green with the comments 'New.' The primary distinctions between the old process and the newly proposed process are as follows:

Firstly, before implementing machine learning demand forecasting, data scientists need to verify whether the products are new or old with historical sales data. For new products lacking historical sales data, stakeholders proposed placing purchase orders (POs) based on customer order quantities and relevant data from the sales department.

Secondly, during data visualization, it was observed that it is crucial to compare demand and supply trends to ensure that supply consistently meets customer demand. Stakeholders recommended continuing to monitor and analyze demand and supply trends.

The following section will explore the implementation plan in the case company.

6.4 Implementation Plan

During validation, stakeholders recognized the significance of implementing the proposal and its benefits for the company. Consensus was reached on three key components: a demand forecasting tool, a demand forecasting process, and an integrated demand forecasting and supply planning process. The implementation plan is presented below.

	Key focus areas from ***CSA***	**Proposals**	**Implementation**	**Responsible**
1	Demand forecasting	In the case company, demand forecasting is essential. We propose using machine learning for forecasting based on historical sales data. For new products without historical sales data, case company will place purchase orders based on end customer orders.	Q3, 2024	Data Scientist, Order fulfilment Specialist.
2	Machine learning	Linear Regression model is proposed for ML demand forecasting for all current products.	Q3, 2024	Data Scientist
		The case company needs to regularly verify the forecasting accuracy which should exceed 90%.	Q3, 2024	Data Scientist
3	Machine learning applied in demand and supply forecasting	The machine learning demand forecasting process is proposed to integrate to the overall demand forecasting and supply planning in the case company.	Q3, 2024	Data Scientist, Order fulfilment Specialist. Operation manager, Sourcing Manager
		It is proposed that the operation team in the case company to hire dedicated scientists for these tasks.	Q3, 2024	VP of Operations

Figure 61. Implementation Plan.

As seen in Figure 61, the initial aspect of the CSA involves the case company's absence of a demand forecasting tool. Acknowledging the criticality of demand forecasting, the company has committed to employing machine learning techniques to forecast all products using historical sales data. For new products, demand predictions will rely on customer orders. The related data will be sourced from the sales department. Implementation is scheduled in Q3, 2024. The data scientists and order fulfillment specialists will be involved in the relevant roles and responsibilities.

Next, the chosen ML model, linear regression, has been identified as the optimal choice for forecasting demand for all the case company's current products. This ML process necessitates achieving an accuracy level exceeding 90%. Implementation is scheduled for Q3, 2024. The data scientists will take the lead role.

Lastly, the integrated demand forecasting and supply planning process is scheduled for implementation in Q3, 2024. The case company intends to recruit dedicated data scientists for the operation team during the same period.

After presenting the implementation plan, the following section will transit into the conclusion.

7 Conclusion

This section provides the study's key findings, managerial implications, and evaluation.

7.1 Executive Summary

The aim of this thesis is to leverage ML algorithms and models to enhance demand forecasting accuracy and assist the case company in inventory reduction and supply optimization. The case company located in Finland and specialized in manufacturing IT -devices. It faces the significant challenge of inaccurate demand forecasts resulting in excess stock and supply shortages. Particularly, one of its key customers, which is a market leader, has considerable bargaining power within the supply chain. The case company struggles with this key customer’s fluctuating weekly demands. It was worsened by the *Bullwhip effect.* It also experiences a significant challenge for precise demand forecasting.

In this thesis, the Applied action research approach is utilized to diagnose the case company’s specific challenges and propose solutions. It begins to define the challenges faced by the case company through an analysis of its current state. Various methods including interviews, meetings, and brainstorming sessions were employed to gather data. By listening to stakeholders’ voice, a process map of demand forecasting and supply planning within the company was constructed. It presented strengths and weaknesses of the current state.

One strength of the case company lies in its utilization of an information-sharing platform called e2open. It presents the exchange of vital data including demands, stock levels, in-transit product quantities, and supplier commitments. Experts in academic field propose that robust information sharing can mitigate the *Bullwhip effect* and foster collaboration across the supply chain. In contrast, a key weakness is the absence of a company-level demand forecasting tool, and it leads to sole reliance on demand data provided by the customer's sharing platform.

After analyzing the current situation, the thesis moves to the literature and best practice review that covers demand forecasting, ML, and ML applied in demand forecasting and supply planning. Firstly, it begins to introduce ML development, ML definition, ML categories. Next, it presents the step-by-step process of constructing a ML model. The process includes data collection, data processing, visualization, feature engineering, algorithm selection, and model validation. Then, it introduced the four most utilized ML models: *Linear Regression, Decision Tree, and Support Vector Machine*. It also outlined the utilization of the ML canvas as a guiding framework for constructing ML models aligned with stakeholders' requirements. Moreover, it provided insights into the practical implementation of ML models in the case company.

During the proposal phase, the ML canvas was used as the guiding framework for developing the ML model. The requirements for the model were aligned with stakeholders and documented in the ML Canvas. What is more, two evaluation metrics were established. Firstly, the ML evaluation metric, where the model demonstrating the lowest MAE and highest R^2 is considered the best one. Secondly, the case company internal metric involving predicted demands divided by sales, with results exceeding 90% considered indicative of a successful model.

Data was extracted from the case company's weekly commitment report. It was originally generated from E2 open. Data preparation involved cleaning and correcting errors. The dataset encompassed weekly demand forecasting reports from 2020 to 2022. The data was split by following an 80-20 rule for training and testing, respectively. Four machine learning algorithms were chosen for model development and training.

The validation process consists of three steps. First, ML evaluation metrics were utilized to assess the models from an Academic perspective. The linear regression model highlighted exceptional performance and achieved an MAE score of 9.68E-14 and an R^2 score of 1. The Decision Tree model attained a MAE score of 7.3 and an R^2 score of 0.99, while the Support Vector Machine scored 418.94 for MAE and -0.2 for R^2. However, the Recurrent Neural Network yielded less favorable results with an MAE score of 653866 and an R^2 score of -1.32. (Dutt et al., 2018.)

Second, the Linear Regression model went through validation for forecasting 2023 demands. By comparing its predictions with the actual sales data from 2023, an accuracy rate exceeding the required 90% was achieved, reaching 93%. Following this comprehensive validation, the machine learning model development process was documented and presented to stakeholders. After review, stakeholders agreed to integrate this process into the initial demand forecasting and supply planning procedures.

The proposed Linear Regression model will be used as a company-level demand forecasting tool to aid decision-makers in accurately predicting demand before placing purchase orders to the suppliers. This will help mitigate the risk of excess stock and shortages caused by inaccurate demand forecasting to a significant extent.

Thirdly, the proposed ML process for demand forecasting, together with the integrated demand forecasting and supply planning process, will offer guidance for ML implementation in demand forecasting. It will contribute to more accurate predictive results.

7.2 Thesis Evaluation

The objective of this thesis is to demonstrate the application of ML models in demand forecasting and supply planning in the case company. By predicting demand more accurately, the ML model can effectively reduce excess stock and optimize supply management. Demand forecasting has significant importance in the case company's supply chains, particularly in scenarios where demand fluctuates and distorts, making effective decision-making challenging. Such fluctuations bring high risks for companies. It often results in excess inventory or shortages, financial losses, customer dissatisfaction, and even loss of customers. Hence, implementing advanced machine learning techniques becomes crucial. It can enhance supply chain efficiency and mitigate associated risks. (Carbonneau et al., 2008; Lee et al., 1997b; Lee et al., 2004.)

Four ML algorithms including *ML Linear Regression, Decision Tree, Recurrent Neural Network, Support Vector Machine* were chosen to construct the predictive model. Data was sourced from weekly demand forecasting reports spanning 2020 to 2022. The dataset was divided according to an 80-20 split, with 80% allocated for training and the remaining 20% for testing and validation. Results revealed that the ML Linear Regression model outperformed others, achieving the highest scores in both Mean Absolute Error (MAE) and R-squared (R^2). Internal validation metrics within the case company confirmed the efficacy of Linear Regression, accurately predicting 2023 demands with a 93% accuracy rate, surpassing the desired threshold of 90%. These findings demonstrate the efficiency and accuracy of ML Linear Regression in demand forecasting. (Dutt et al., 2018.)

This study encounters challenges related to the complexity and rapid evolution of ML techniques and tools. Although ML finds application in various industries like autonomous driving, movie recommendation, speech recognition, and spam mail detection (Ng, 2023), its adoption in supply chain and demand forecasting contexts in real-world business environments remains limited.

Future projects can be done into two directions. First, ML encompasses a wide array of algorithms. Guided by literature review and in collaboration with data scientists from the case company, this study focused on the selection of only four algorithms for model construction. However, it is recommended that in future endeavors, additional algorithms such as *Multilinear Regression*, *Polynomial Regression, Random Forest, and Naïve Bayes Logistic Regression* can be also considered for inclusion in demand forecasting model building. (Dutt et al., 2018.)

Second, this thesis employed four machine learning algorithms for demand forecasting. Among them, the *Linear Regression* model demonstrated superior performance based on both ML and internal validation metrics. However, the reason behind this superiority was not included in the thesis. Future projects should delve into exploring this phenomenon further. Rožanec et al., (2021) had the comments in their study as follows.

> "*Accurate forecasts are a precondition to building users' trust in a demand forecasting software. Moreover, ML models explain ability is required to help the user understand the reasons behind a forecast, decide if it can be trusted, and gain more profound domain knowledge*." (Rožanec et al., 2021.)

Hence, this study serves as an example for those interested in conducting applied projects in similar domains.

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Appendix

Python Scripts

Decision Tree

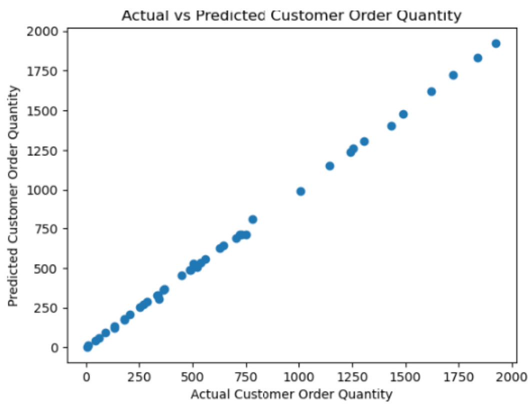
```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import mean_absolute_error, r2_score
import matplotlib.pyplot as plt

# Read the CSV file into a pandas DataFrame
data = pd.read_csv('AlldataSummary.csv')

# Display the first few rows of the dataframe
print(data.head())

# Preprocessing the data
# Assuming 'year', 'week', 'customer_stock_quantity', 'customer_order_quantity', 'product_code', 'price', and 'region' are the column names

# Convert 'year' and 'week' to datetime format
data['date'] = pd.to_datetime(data['Year'].astype(str) + data['W'].astype(str) + '1', format='%Y%W%w')

# Selecting relevant features and target variable
X = data[['Customer_stock', 'Customer_orders', 'Price']]  # Features
y = data['Customer_stock']  # Target variable

# Splitting data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Training the model
model = DecisionTreeRegressor(random_state=42)
model.fit(X_train, y_train)

# Making predictions
y_pred = model.predict(X_test)

# Model evaluation using mean absolute error (MAE)
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
print('Mean Absolute Error:', mae)
print('Coefficient of Determination (R^2):', r2)

# Plotting actual vs predicted values
plt.scatter(y_test, y_pred)
plt.xlabel('Actual Customer Order Quantity')
plt.ylabel('Predicted Customer Order Quantity')
plt.title('Actual vs Predicted Customer Order Quantity')
plt.show()

# Plotting residuals
residuals = y_test - y_pred
plt.scatter(y_pred, residuals)
plt.axhline(y=0, color='r', linestyle='--')
plt.xlabel('Predicted Customer Order Quantity')
plt.ylabel('Residuals')
plt.title('Residual Plot')
plt.show()

# Plotting the distribution of residuals
plt.hist(residuals, bins=30)
plt.xlabel('Residuals')
plt.ylabel('Frequency')
plt.title('Distribution of Residuals')
plt.show()
```

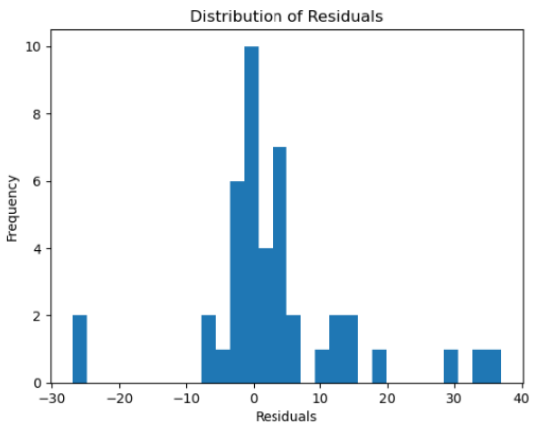
Results of Decision Tree

	Year	W	Customer_stock	Customer_orders	Product	Price	Region
0	2020	7	386	27	1	1	1
1	2020	8	399	35	1	1	1
2	2020	9	382	174	1	1	1
3	2020	12	132	247	1	1	1
4	2020	14	556	1544	1	1	1

Mean Absolute Error: 7.3023255813953485

Coefficient of Determination (R^2): 0.9994821345466534





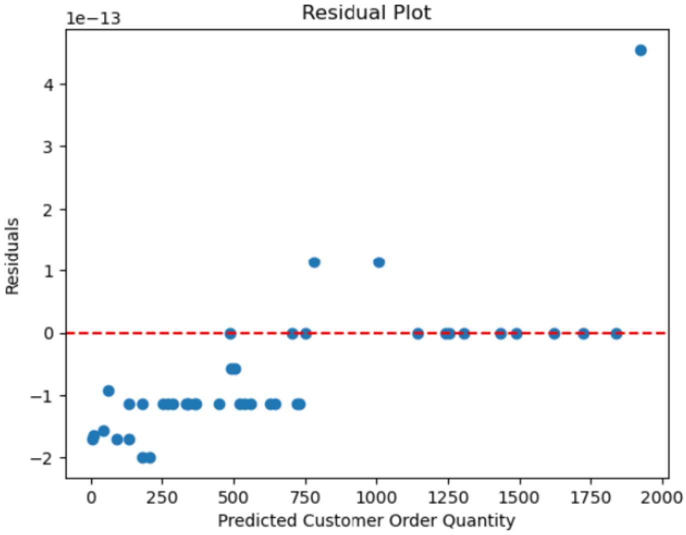
Linear Regression

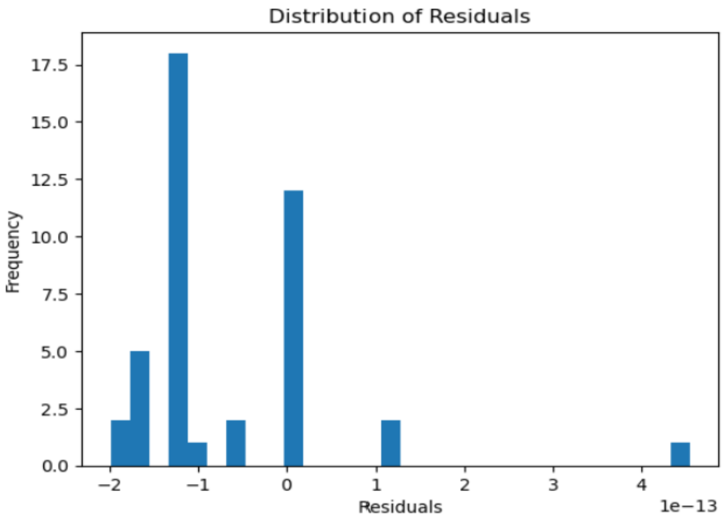
```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, r2_score
import matplotlib.pyplot as plt

# Read the CSV file into a pandas DataFrame
data = pd.read_csv('AlldataSummary.csv')

# Display the first few rows of the dataframe
print(data.head())

# Preprocessing the data
# Assuming 'year', 'week', 'customer_stock_quantity', 'customer_order_quantity', 'product_code', 'price', and 'region' are the column names

# Convert 'year' and 'week' to datetime format
data['date'] = pd.to_datetime(data['Year'].astype(str) + data['W'].astype(str) + '1', format='%Y%W%w')

# Selecting relevant features and target variable
X = data[['Customer_stock', 'Customer_orders', 'Price']]  # Features
y = data['Customer_stock']  # Target variable

# Splitting data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Training the model
model = LinearRegression()
model.fit(X_train, y_train)

# Making predictions
y_pred = model.predict(X_test)

# Model evaluation using mean absolute error (MAE)
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
print('Mean Absolute Error:', mae)
print('Coefficient of Determination (R^2):', r2)

# Plotting actual vs predicted values
plt.scatter(y_test, y_pred)
plt.xlabel('Actual Customer Order Quantity')
plt.ylabel('Predicted Customer Order Quantity')
plt.title('Actual vs Predicted Customer Order Quantity')
plt.show()

# Plotting residuals
residuals = y_test - y_pred
plt.scatter(y_pred, residuals)
plt.axhline(y=0, color='r', linestyle='--')
plt.xlabel('Predicted Customer Order Quantity')
plt.ylabel('Residuals')
plt.title('Residual Plot')
plt.show()

# Plotting the distribution of residuals
plt.hist(residuals, bins=30)
plt.xlabel('Residuals')
plt.ylabel('Frequency')
plt.title('Distribution of Residuals')
plt.show()
```

Results of Linear Regression

	Year	W	Customer_stock	Customer_orders	Product	Price	Region
0	2020	7	386	27	1	1	1
1	2020	8	399	35	1	1	1
2	2020	9	382	174	1	1	1
3	2020	12	132	247	1	1	1
4	2020	14	556	1544	1	1	1

```
Mean Absolute Error: 9.683210305939997e-14
Coefficient of Determination (R^2): 1.0
```





Recurrent Neural Network

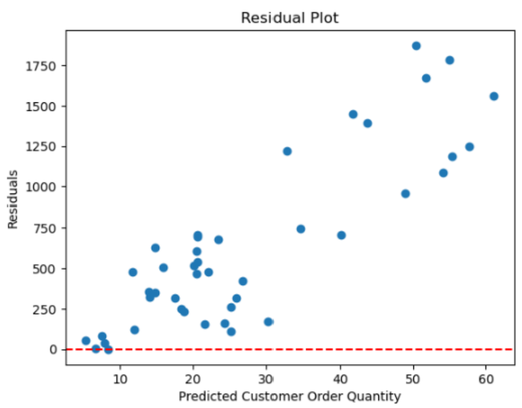
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_squared_error, r2_score
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense
import matplotlib.pyplot as plt

# Read the CSV file into a pandas DataFrame
data = pd.read_csv('AlldataSummary.csv')

# Display the first few rows of the dataframe
print(data.head())

# Preprocessing the data
# Assuming 'year', 'week', 'customer_stock_quantity', 'customer_order_quantity', 'product_code', 'price', and 'region' are the column names

# Convert 'year' and 'week' to datetime format
data['date'] = pd.to_datetime(data['Year'].astype(str) + data['W'].astype(str) + '1', format='%Y%W%w')

# Selecting relevant features and target variable
X = data[['Customer_stock', 'Customer_orders', 'Price']]  # Features
y = data['Customer_stock']  # Target variable

# Splitting data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Feature scaling
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Reshape input data to fit the LSTM input shape
X_train_reshaped = np.reshape(X_train_scaled, (X_train_scaled.shape[0], 1, X_train_scaled.shape[1]))
X_test_reshaped = np.reshape(X_test_scaled, (X_test_scaled.shape[0], 1, X_test_scaled.shape[1]))

# Building the LSTM-based RNN model
model = Sequential([
    LSTM(64, input_shape=(X_train_reshaped.shape[1], X_train_reshaped.shape[2]), activation='relu'),
    Dense(1)
])

# Compile the model
model.compile(optimizer='adam', loss='mean_squared_error')

# Train the model
history = model.fit(X_train_reshaped, y_train, epochs=100, batch_size=32, validation_split=0.2, verbose=0)

# Evaluate the model
y_pred = model.predict(X_test_reshaped)
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
print('Mean Squared Error:', mse)
print('Coefficient of Determination (R^2):', r2)

# Plotting actual vs predicted values
plt.scatter(y_test, y_pred)
plt.xlabel('Actual Customer Order Quantity')
plt.ylabel('Predicted Customer Order Quantity')
plt.title('Actual vs Predicted Customer Order Quantity')
plt.show()

# Plotting residuals
residuals = y_test - y_pred.flatten()
plt.scatter(y_pred.flatten(), residuals)
plt.axhline(y=0, color='r', linestyle='--')
plt.xlabel('Predicted Customer Order Quantity')
plt.ylabel('Residuals')
plt.title('Residual Plot')
plt.show()

# Plotting the distribution of residuals
plt.hist(residuals, bins=30)
plt.xlabel('Residuals')
plt.ylabel('Frequency')
plt.title('Distribution of Residuals')
plt.show()
```

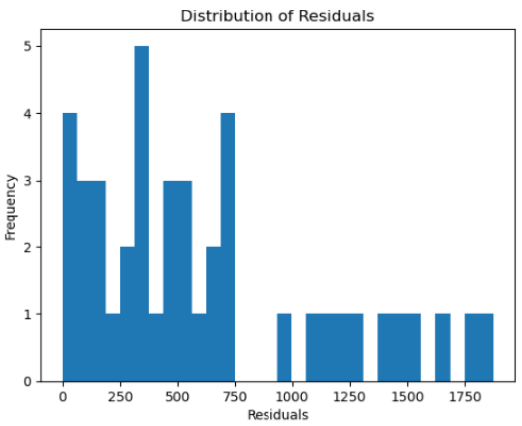
Results of Recurrent Neural Network

	Year	W	Customer stock	Customer orders	Product	Price	Region
0	2020	7	386	27	1	1	1
1	2020	8	399	35	1	1	1
2	2020	9	382	174	1	1	1
3	2020	12	132	247	1	1	1
4	2020	14	556	1544	1	1	1

Mean Squared Error: 658328.1911790693

Coefficient of Determination (R^2): -1.3433173543097392





Support Vector Machine

```
from sklearn.svm import SVR
from sklearn.metrics import mean_absolute_error, r2_score
import matplotlib.pyplot as plt

# Read the CSV file into a pandas DataFrame
data = pd.read_csv('AlldataSummary.csv')

# Display the first few rows of the dataframe
print(data.head())

# Preprocessing the data
# Assuming 'year', 'week', 'customer_stock_quantity', 'customer_order_quantity', 'product_code', 'price', and 'region' are the column names

# Convert 'year' and 'week' to datetime format
data['date'] = pd.to_datetime(data['Year'].astype(str) + data['W'].astype(str) + '1', format='%Y%W%w')

# Selecting relevant features and target variable
X = data[['Customer_stock', 'Customer_orders', 'Price']]  # Features
y = data['Customer_stock']  # Target variable

# Splitting data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Training the SVR model
svr = SVR(kernel='rbf', C=100, gamma='auto')  # You can adjust hyperparameters here
svr.fit(X_train, y_train)

# Making predictions
y_pred = svr.predict(X_test)

# Model evaluation using mean absolute error (MAE)
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
print('Mean Absolute Error:', mae)
print('Coefficient of Determination (R^2):', r2)

# Plotting actual vs predicted values
plt.scatter(y_test, y_pred)
plt.xlabel('Actual Customer Order Quantity')
plt.ylabel('Predicted Customer Order Quantity')
plt.title('Actual vs Predicted Customer Order Quantity')
plt.show()

# Plotting residuals
residuals = y_test - y_pred
plt.scatter(y_pred, residuals)
plt.axhline(y=0, color='r', linestyle='--')
plt.xlabel('Predicted Customer Order Quantity')
plt.ylabel('Residuals')
plt.title('Residual Plot')
plt.show()

# Plotting the distribution of residuals
plt.hist(residuals, bins=30)
plt.xlabel('Residuals')
plt.ylabel('Frequency')
plt.title('Distribution of Residuals')
plt.show()
```

Results of Suport Vector Machine

```
Year   W  Customer_stock  Customer_orders  Product  Price  Region
0  2020   7             386               27        1       1       1
1  2020   8             399               35        1       1       1
2  2020   9             382              174        1       1       1
3  2020  12             132              247        1       1       1
4  2020  14             556             1544        1       1       1
Mean Absolute Error: 339534.11995671235
Coefficient of Determination (R^2): -0.208570749871519 47
```