ITE2010 – ARTIFICIAL INTELLIGENCE

REVIEW – 2

TOPIC: SMART INVENTORY MANAGEMENT SYSTEM

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I. ABSTRACT

The Smart Inventory Management System predicts the demand of a particular product and allows the user to see the future growth as well as analyse how much raw material is required to be ordered/purchased for the same. The daily demand of 1 year is taken into account to populate the dataset and daily demand is predicted using a python script.

Demand can be represented using plots and can also be computed numerically. This can be beneficial as no extra money will be wasted on raw materials and also can free up the inventory.

II. OBJECTIVES

- To predict daily demand
- To compute amount of raw material to be ordered

III. INTRODUCTION

Small Scale Industries (SSIs) account for nearly 55% of the total industries in our country. Most of these are rural population owned where principal amount to start such business is low. So, to streamline the expenditure and stabilize the profit and investment ratio, we can use a smart inventory management system. The model uses machine learning to extract the dataset populated with the daily demand of the products in the inventory and process it with predictive analysis to compute the predicted growth of the demand.

3.1. LITERATURE REVIEW

Du et al. [1] (2019), stated that research interests in machine learning (ML) and supply chain management (SCM) have yielded an enormous amount of publications during the last two decades. The aim of this study is to provide a comprehensive view of ML applications in SCM, working as a reference for future research directions for SCM researchers and application insight for SCM practitioners. ML is a subbranch of AI that equips the machines with the capability to automatically learn from the data existing with no specific programming. Based on the learning methods, the research design is classified into supervised learning, unsupervised learning and reinforcement learning. The research finds that the most frequently used research design is supervised learning (87%), followed by unsupervised learning (8%) and reinforcement learning (5%). It is worth noting that only 10 out of 32 commonly recognized ML algorithms have been frequently applied in SCM. The 10 most commonly used algorithms identified were Decision Trees, Random Forest, K-means, K-Nearest Neighbor, Logistic Regression, Naïve Bayes, Neural Networks, Support Vector Machine, Ensemble Algorithms and Extreme Learning Machines. Out of these, the most commonly used algorithms were Neural Networks (54%) and Support Vector Machines (22%). These algorithms are used in 6 major areas which have been identified as Demand/sales estimation, Procurement and supply management, Production, Transportation and distribution, Inventory and storage and Supply chain improvement.

Pawet [2] (2016), presents a proposal for a combined application of fuzzy logic and genetic algorithms to control the procurement process in the enterprise. The approach presented in this paper draws particular attention to the impact of external random factors in the form of demand and lead time uncertainty. The model uses time-variable membership function parameters in a dynamic fashion to describe the modelled output fuzzy (sets) values. An additional element is the use of genetic algorithms for optimization of fuzzy rule base in the proposed method. The approach presented in this paper was verified according to four criteria based on a computer simulation performed on the basis of the actual data from an enterprise.

Tereza [3] (2016), said that to examine suitable methods of artificial neural networks and their application in business operations, specifically to the supply chain management. The article discusses construction of an artificial neural networks model that can be used to facilitate optimization of inventory level and thus improve the ordering system and inventory management. For the data analysis from the area of wholesale trade with connecting material is used. Methods used in the paper consists especially of artificial neural networks and ANN-based modelling. For data analysis and preprocessing, MS Office Excel software is used. As an instrument for neural network forecasting MathWorks MATLAB Neural Network Tool was used. Deductive quantitative methods for research are also used. The effort is directed at finding whether the method of prediction using artificial neural networks is suitable as a tool for enhancing the ordering system of an enterprise. The research also focuses on finding what architecture of the artificial neural networks model is the most suitable for subsequent prediction. Artificial neural networks models can be used for inventory management and lot-sizing problem successfully. A network with the TRAINGDX training function and TANSIG transfer function and 6-8-1 architecture can be considered the most suitable for artificial neural network, as it shows the best results for subsequent prediction. It can be concluded that the created model of artificial neural network can be successfully used for predicting order size and therefore for improving the order cycle of an enterprise.

Bo [4] (2010), demonstrated that product take-back legislation forces manufacturers to bear the costs of collection and disposal of products that have reached the end of their useful lives. In order to reduce these costs, manufacturers can consider reuse, remanufacturing and/or recycling of components as an alternative to disposal. The implementation of such alternatives usually requires an appropriate reverse supply chain management. With the concepts of reverse supply chain gaining popularity in practice, the use of artificial intelligence approaches in these areas is also becoming popular. As a result, the purpose of this paper is to give an overview of the recent publications concerning the application of artificial intelligence techniques to reverse supply chain with emphasis on certain types of product returns.

Resul et al. [5] (2020), stated that supply and demand are two fundamental concepts of sellers and customers. Predicting demand accurately is critical for organizations in order to be able to make plans. In this paper, the authors propose a new approach for demand prediction on an e-commerce web site. The proposed model differs from earlier models in several ways. The business model used in the e-commerce web site, for which the model is implemented, includes many sellers that sell the same product at the same time at different prices where the company operates a market place model.

The demand prediction for such a model should consider the price of the same product sold by competing sellers along the features of these sellers. In this study the authors first applied different regression algorithms for a specific set of products of one department of a company that is one of the most popular online e-commerce companies in Turkey. Then they used stacked generalization also known as stacking ensemble learning to predict demand. Finally, all the approaches were evaluated on a real-world data set obtained from the e-commerce company. The experimental results show that some of the machine learning methods do produce almost as good results as the stacked generalization method.

Benjamin [6] (1997), discusses an application of neuro-dynamic programming techniques for the optimization of retailer inventory systems. It describes a specific case study involving a model with thirty-three states. The enormity of this state space renders classical algorithms of dynamic programming inapplicable. The performance of solutions generated by neuro-dynamic programming algorithms are compared to that delivered by optimized s-type ("order-up-to") policies. The study enables the generation of substantially superior control strategies which helps in reducing inventory costs by approximately ten percent.

George [7] (2019), showed supply chain risk management (SCRM) encompasses a wide variety of strategies aiming to identify, assess, mitigate and monitor unexpected events or conditions which might have an impact, mostly adverse, on any part of a supply chain. SCRM strategies often depend on rapid and adaptive decision-making based on potentially large, multidimensional data sources. These characteristics make SCRM a suitable application area for artificial intelligence (AI) techniques. The aim of this paper is to provide a comprehensive review of supply chain literature that addresses problems relevant to SCRM using approaches that fall within the AI spectrum. To that end, an investigation is conducted on the various definitions and classifications of supply chain risk and related notions such as uncertainty. Then, a mapping study is performed to categorize existing literature according to the AI methodology used, ranging from mathematical programming to Machine Learning and Big Data Analytics, and the specific SCRM task they address (identification, assessment or response). Finally, a comprehensive analysis of each category is provided to identify missing aspects and unexplored areas and propose directions for future research at the confluence of SCRM and AI.

Gérard et al. [8] (2000), stated that in traditional supply chain inventory management, orders are the only information firms exchange, but information technology now allows firms to share demand and inventory data quickly and inexpensively. The study assesses the value of sharing these data in a model with one supplier, N identical retailers, and stationary stochastic consumer demand. There are inventory holding costs and back-order penalty costs. The study compares a traditional information policy that does not use shared information with a full information policy that does exploit shared information. In a numerical study it is found that supply chain costs are 2.2% lower on average with the full information policy than with the traditional information policy, and the maximum difference is 12.1%. A simulation-based lower bound over all feasible policies is also developed. The cost difference between the traditional information policy and the lower bound is an upper bound on the value of information sharing: In the same study, that difference is 3.4% on average, and no more than 13.8%. The study contrasts the value of information sharing with two other benefits of information technology, faster and cheaper order processing, which lead to shorter lead times and smaller batch sizes, respectively. In the sample, cutting lead times nearly in half reduces costs by 21% on average, and cutting batches in half reduces costs by 22% on average. For the settings studies, it is concluded that implementing information technology to accelerate and smooth the physical flow of goods through a supply chain is significantly more valuable than using information technology to expand the flow of information.

Jin et al. [9] (2016), demonstrated that with the emergence of individualized and personalized customer demands, the interaction of service and product has come into the sight of manufacturers and thus promoted the arising of service-oriented manufacturing (SOM), a new business mode that combines manufacturing and service. Similar to the conventional manufacturing, the customer demand prediction (CDP) of SOM is very important since it is the foundation of the following manufacturing stages. As there are always tight and frequent interactions between service providers and customers in SOM, the customer satisfaction would significantly influence the customer demand of the following purchasing periods. To cope with this issue, a novel CDP approach for SOM incorporating customer satisfaction is proposed. Firstly, the structural relationships among customer satisfaction index and the influence factors are quantitatively modelled by using the structural equation model. Secondly, to reduce the adverse effect of multiple structural input data and small sample size, the least square support vector mechanism is employed to predict customer demand. Finally, the CDP of the air conditioner compressor which is a typical SOM product is implemented as the real-case example, and the effectiveness and validity of the proposed approach is elaborated from the prediction results analysis and comparison.

Xin et al. [10] (2004), published that traditional inventory models focus on risk-neutral decision makers, i.e., characterizing replenishment strategies that maximize expected total profit, or equivalently, minimize expected total cost over a planning horizon. The study proposes a framework for incorporating risk aversion in multiperiod inventory models as well as multiperiod models that coordinate inventory and pricing strategies. It shows that the structure of the optimal policy for a decision maker with exponential utility functions is almost identical to the structure of the optimal risk-neutral inventory (and pricing) policies. These structural results are extended to models in which the decision maker has access to a (partially) complete financial market and can hedge its operational risk through trading financial securities. Computational results demonstrate that the optimal policy is relatively insensitive to small changes in the decision-maker's level of risk aversion.

Ilaria et al. [11] (2002), stated that a major issue in supply chain inventory management is the coordination of inventory policies adopted by different supply chain actors, such as suppliers, manufacturers, distributors, so as to smooth material flow and minimize costs while responsively meeting customer demand. This paper presents an approach to manage inventory decisions at all stages of the supply chain in an integrated manner. It allows an inventory order policy to be determined, which is aimed at optimizing the performance of the whole supply chain. The approach consists of three techniques: (i) Markov decision processes (MDP) and (ii) an artificial intelligent algorithm to solve MDPs, which is based on (iii) simulation modeling. In particular, the inventory problem is modeled as an MDP and a reinforcement learning (RL) algorithm is used to determine a near optimal inventory policy under an average reward criterion. RL is a simulation-based stochastic technique that proves very efficient particularly when the MDP size is large.

Kochak et al. [12] (2015), showed that the demand forecasting technique which is modelled by artificial intelligence approaches using artificial neural networks. The consumer product causers the difficulty in forecasting the future demand and the accuracy of the forecast in performance of the artificial neural network an advantage in a constantly changing business environment and demand forecasting an organization in order to make right decisions regarding manufacturing and inventory management. The learning algorithm of the prediction is also imposed to better prediction of time series in future. The prediction performance of recurrent neural networks a simulated time series data and a practical sales data have been used. This is because of influence of several factors on demand function in retail trading system. It was also observed that as forecasting period becomes smaller, the ANN approach provides more accuracy in forecast.

Jing et al. [13] (2013), introduced the characteristics and basic application of RFID technology, analyses the data flow of intelligent inventory system from the perspective of business and function, then puts forward the specific framework programs and function modules of intelligent inventory management system based on IOT RFID technology, focuses on elaborating the design and implementation process of the intelligent inventory system. The system realizes full control and management of all products, faster in/out warehouse and dynamic inventory, utilizes warehouse efficiently and improves the capacity of warehouse by effective combining with the ERP system in enterprise.

Lipshutz et al. [14] (1991), showed that the Logistics Inventory Management System is an expert system to assist Unisya spare parts inventory analysts in developing an action plan on a part by part basis to maintain inventory levels within a target zone. The task is complex and has significant cost impact. LIMA is a PC-hosted tool, incorporating business presentation graphics, statistical analysis, “what if ... “capabilities and expert assistance from a Prolog knowledge base. Data provided to LIMA are extracted from a large mainframe database of parts usage. The expert system component guides the analyst through a data validation process, generates an action plan to cover the planning period and engages the analyst in a planning dialogue.

Hokey [15] (2010), published that artificial intelligence (AI) was introduced to develop and create "thinking machines" that are capable of mimicking, learning, and replacing human intelligence. Since the late 1970s, AI has shown great promise in improving human decision-making processes and the subsequent productivity in various business endeavours due to its ability to recognize business patterns, learn business phenomena, seek information, and analyze data intelligently. Despite its widespread acceptance as a decision-aid tool, AI has seen limited application in supply chain management (SCM). To fully exploit the potential benefits of AI for SCM, this paper explores various sub-fields of AI that are most suitable for solving practical problems relevant to SCM. In so doing, this paper reviews the past record of success in AI applications to SCM and identifies the most fruitful areas of SCM in which to apply AI.

Yashoda [16] (2018), demonstrated that with accumulation and proliferation of large data, it is highly necessary to make some meaningful sense out of the data. Here is where Artificial Intelligence (AI) tools and algorithms play a major role. AI is highly expertise in handling the customer data and forecasting the purchase behavior of customers. This has brought out the biggest level of automation in the ecommerce industry. AI provide notification when a company has to re-order stock and assist in creating manufacturing schedule as per the variation in demand during the particular period of time accurately. The autonomous and data-driven supply chain has optimized logistics, manufacturing, warehousing and the last mile delivery. E-commerce giant like Amazon use leads to time and forecasting techniques to critically plan inventory orders. Machine learning system (MLS), a subset of AI solves the cognitive problems associated with human intelligence and helps to optimize logistic speed and quality. This paper discusses AI-based inventory management tools which are being utilized in the e-commerce industry. AI provides customers an enriched experience which helps to maximize profits.

Woschank et al. [17] (2020), showed that industry 4.0 concepts and technologies ensure the ongoing development of micro and macro-economic entities by focusing on the principles of interconnectivity, digitalization, and automation. In this context, artificial intelligence is seen as one of the major enablers for Smart Logistics and Smart Production initiatives. This paper systematically analyzes the scientific literature on artificial intelligence, machine learning, and deep learning in the context of Smart Logistics management in industrial enterprises. Furthermore, based on the results of the systematic literature review, the authors present a conceptual framework, which provides fruitful implications based on recent research findings and insights to be used for directing and starting future research initiatives in the field of artificial intelligence (AI), machine learning (ML), and deep learning (DL) in Smart Logistics.

Boru et al. [18] (2019), showed in this paper, a new hybrid method including simulation optimization and artificial intelligence-based simulation is created to solve the inventory routing problem (IRP) in which three different routing strategies are evaluated for uneven demand patterns including intermittent, erratic, and lumpy demand. The proposed method includes two phases. In the first phase, a nondominated sorting genetic algorithm II-based simulation is employed to perform a multi-objective search for the IRP where the objectives of the method are total supply chain cost minimization and average service level maximization. In the second phase, artificial neural network-based simulation is used to adjust the reorder point and order-up-to-level by forecasting the customer demand at each replenishment time. The results of the study demonstrated that the average service level is at least 98.54% in the supply chain. From this, it can be concluded that the proposed method can provide a tremendous opportunity to improve the average service level under uncertain environments. In addition, it is determined that different routing strategies can be selected for different demand patterns according to the considered performance measures.

Praveen et al. [19] (2020), showed that a major requirement for small/medium-sized businesses is Inventory Management since a lot of money and skilled labor has to be invested to do so. E-commerce giants use Machine Learning models to maintain their inventory based on demand for a particular item. Inventory Management can be extended as a service to small/medium sized businesses to improve their sales and predict the demand of various products. Demand forecasting is a crucial part of all businesses and brings up the following question: How much stock of an item should a company/business keep to meet the demands, i.e., what should the predicted demand of a product be? Among its many benefits, a predictive forecast is a key enabler for a better customer experience through the reduction of out-of-stock situations, and for lower costs due to better planned inventory and less write-off items. The paper discusses the challenges of building an Inventory system and discusses the design decisions.

Min-Chun [20] (2011), published that ABC analysis is a popular and effective method used to classify inventory items into specific categories that can be managed and controlled separately. Conventional ABC analysis classifies inventory items three categories: A, B, or C based on annual dollar usage of an inventory item. Multi-criteria inventory classification has been proposed by a number of researchers in order to take other important criteria into consideration. These researchers have compared artificial-intelligence (AI)-based classification techniques with traditional multiple discriminant analysis (MDA). Examples of these AI-based techniques include support vector machines (SVMs), backpropagation networks (BPNs), and the *k*-nearest neighbours (*k*-NN) algorithm. To test the effectiveness of these techniques, classification results based on four benchmark techniques are compared. The results show that AI-based techniques demonstrate superior accuracy to MDA. Statistical analysis reveals that SVM enables more accurate classification than other AI-based techniques. This finding suggests the possibility of implementing AI-based techniques for multi-criteria ABC analysis in enterprise resource planning (ERP) systems.

Muhammad et al. [21] (2015), showed that Enterprise Resource Planning (ERP) systems provides function to calculate Safety Stock (SS), demand forecast and determine Reorder Point (ROP) for each product in the stock. The earlier used systems lack proper accuracy for slow moving items like spare products. The proposed model uses pooled distribution, instead of Poisson distribution, according to similarities in the demand history and lead times of spare products. This is more feasible and practical alternative to complex theoretical distributions. The advantage of this model is it is easier to implement and integrate with the existing ERP systems compared to other frequently used models. The disadvantage of the said model is with time, the group probability distribution of the spare items must be calculated periodically. Also, obsolescence cost and variable lead time aren't taken into account in the model.

Woschank et al. [22] (2020), wrote in this paper that smart logistics aims at the successful implementation of intelligent and lean supple chains based on agile and cooperative networks and interlinked organizations. This paper conducts a systematic literature review of recent studies regarding the application of ML, AI and DL in smart logistics. It is found that the technology is still in its early stages. Most of the developments are conceptual and in early testing phase. The technologies found were Strategic and Tactical Process Optimization, Cyber-Physical Systems, Predictive maintenance, Hybrid decision support systems, production planning and control systems and intelligent transport logistics. These topics lack mature industrial applications. Therefore, for further development other fields such as IT, logistics, mechanical engineering, statistics, etc. must be integrated.

Hanson et al. [23] (2019), published that Big data is the usage of the vast structured and unstructured data generated by a system. AI is the use of computers to execute decisions which are "smart" in nature, i.e. self-made decision based on some pattern or algorithm. Big data is used by industries to collect the enterprise data from all the ERP systems, verify and clean it. AI is used in Supply Chain Management to forecast demand, develop new business models and identification of radical customization of services. It is concluded that to achieve and retain customer confidence and trust, organizations that use AI and Big data need to be able to present the authenticity of the data generated. Effective use of AI and big data presents opportunities to organizations to develop the business to be human-free and also be according to the customer market.

Pervaiz [24] (2020), showed how the man-made reasoning or AI is functioning in the Supply Chain Management. It is found that AI is very much integrated with the systems related to SCM. The use of chat-bots to automate replies is quite common. Smart warehouses are used to automate the inventory management which leads to increased revenue. Genetic algorithms are used to improve delivery times and reducing costs by finding the shortest paths. It is concluded that AI has brought about a major change in the industry which has led to an increased efficiency.

Toktay et al. [25] (2000), demonstrated that remanufacturing is the process of using products which are recovered, processed and sold as new products. The proposed model is used to develop a supply chain for Kodak's single-use camera, from the overseas production of circuit boards to the photofinishing lab's development of the film and subsequent return to the camera factory. Queueing network is used to model production and distribute facilities whereas, statistical aspects of problem are dynamically estimated like the probability that sold cameras are returned, delay of returned cameras etc. The model lacks the usage of customer demand i.e. seasonal demand and unsatisfied demand are unaccounted which leads to a doubt on the overall efficacy of the proposed system to solve a real-world problem.

Yashoda [26] (2018), showed that e-commerce involves buying and selling of goods on the internet platforms. Other than money transactions, timely transportation of goods is required too. This calls for a smart supply chain. Big companies in E-commerce like Flipkart and Amazon are expanding their horizons with the use of AI. Amazon uses it to predict customer behavior and required inventory. Machine learning is used to analyze market campaigns and predict inventory. Amazon Machine Learning Algorithm has reduced the complexities of traditional forecasting models and has provided better speeds and accuracy. Overall, AI has revolutionized the e-commerce sector with its high accuracy and real time analysis. This has led to better understanding of customer patterns and increased the profits.

Michalski [27] (2008), demonstrated how traditional inventory management models work at providing a basic aim of every business: maximize its profit. The proposed model helps achieve one more aim along with the existing ones: maximize the value of the business. The paper provides modifications to both the value-based EOQ (Economic Order Quantity) model and value-based POQ (Production Order Quantity) model. The aim of this model is to find a balance between keeping high inventory to increase profits by sales but also increasing the risk, and keeping excess cash in inventory. The proposed model by bringing this balance makes for better value-based decisions for the firm.

Matthew et al. [28] (2013), stated Data Science, predictive analytics and big data, the confluence of them commonly called BDP is the up and coming trend in the world of SCM (Supply Chain Management). Data is considered to be driver of better decision-making process. Organizations using BDP are on average 5% more productive and 6% more profitable. The research portrays the current development in the fields of data science, predictive analysis and big data in supply chain industry. It is used to calculate statistics, predict demand, optimize events, calculate probabilities. Data mining is a major aspect of the current applications. Customer behavior is understood through the collected data to optimize and analyze marketing, supply and customize the products. It is also discussed about DPB as a profession and a rising demand for DPB professionals in the market.

Jianqian et al. [29] (2014), said estimation and forecasting demand in a dynamic market is required to scale ethe business and also sustain it. Therefore, statistical demand prediction models are on the rise. The paper deals with the demand prediction model for laptops sold by HP. The developed model uses regression trees and a varying-coefficient mode. The proposed method starts with a tree model that partitions the space of varying-coefficient variables, then uses boosting to improve the predictive performance as well as the regression coefficient. The performance of the proposed approach was examined in a simulation with an application to the marketing data. The dependence of the demand on the product prices are carefully plotted for different brands to find a correlation that can lead to better pricing of the products. This brings about a positive change in the form of increased demand. Various boosting algorithms are also tested to find out one with the maximum efficiency which is found out to be BRAND.

Wenzel et al. [30] (2019), published in this paper the current trend in the development of Machine Learning (ML) is the integration with Supply Chain Management (SCM) to form smart systems which can automate and improve efficiency of the SCM task model. The paper looks into the current developments and applications of ML in SCM and visualizes probable research gaps. It was demonstrated that in the SCM task model a single area could have different ML methods applied for a common goal. A large portion of the research is focused primarily on demand prediction. An investigation of ML methods for inter-company areas such as SRM and CRM could be promising for SCM. Majority of the research work is still conceptual and requires integration with the SCM model to be useful and widespread. The deployment phase lacks enough emphasis.

Zdravkovic [31] (2014), demonstrated artificial is the ability to perform complex intellectual tasks like humans by a machine. Machine learning is the ability portrayed by a machine to learn how to perform a task. The commonly used AI and ML systems in supply chain are demand forecasting and inventory planning, material sourcing, manufacturing decisions, quality assurance and delivery and logistics. Other than demand of products, the likeable features can also be explored through machine learning. Amazon uses autonomous fork lifts in its warehouse operations. Some organizations like amazon and uber eats are trying put self-driving/smart robots to provide delivery of goods. It is also used to analyze HR and finance data to find out about anomalies in the data, to verify documents and check employee details.

Rahul [32] (2016), said Artificial Intelligence is always used to solve complex problems which are beyond human computational skills. The sub-disciplines of AI such as GA's and expert systems are employed to address complex issue of Supply Chain Management. It involves inventory management, location planning, purchasing, freight consolidation and routing or scheduling problems. Expert systems a sub-discipline of AI, is used to help purchasing managers to evaluate the performance of prospective suppliers, optimize the information exchange amongst purchase personnel and reduces the time taken to make the make-or-buy decision. AI is completely armed with predictive analytics that can analyze clusters of data collected through various sources. Analyzing these data helps companies to develop an efficient form of supply chain management.

Raghav [33] (2019), demonstrated how Supply Chain Management is critical in almost every industry today and there is an increased interest to revolutionize it using AI applications, from its benefits to fully leveraging the vast amounts of data collected by industrial logistics, warehousing and transport systems. LLamasoft is an organization providing solutions to predictive analytics for demand forecasting. Its Demand Guru predictive modeling software uses Machine Learning to identify hidden patterns such as seasonal demand or correlations between external weather, demand and other influences in historical demand data to help businesses identify ways to cut costs and increase operational efficiency across their supply chains. Chyme by Univired is a chatbot which is a conversational interface used to communicate between human operators and sales/marketing automation services such as SAP’s salesforce.

Elton et al. [34] (2018), stated that in the recent years AI has risen to be the major trend in automating systems to streamline efficiency and profit. Procurement and supply chains, along with the wealth of data they generate, are both ripe to
leverage the efficiencies and insights afforded by AI, and in some cases already are. Different areas of Supply Chain have been driven with AI. These include: Requisition/ PO processing, PO Acknowledgement and Delivery Assurance, Catalogue Management, Guided Buying, Invoice Processing and Payment, Help Desk and Support. As technology progresses more and more businesses and systems will adopt AI as it has a promising future.

Mansoor [35] (2020), evaluated how AI is revamping the operational process and facilitating cost-effective supply chain solutions. It provides analysis of leading companies and solutions that are leveraging AI in their supply chains and those they manage on behalf of others, with evaluation of key strengths and weaknesses of these solutions. The report also provides a view into the future of AI in Supply Chain Management (SCM) including analysis of performance improvements such as optimization of revenues, supply chain satisfaction, and cost reduction. The report provides detailed analysis and forecasts for AI in SCM by solution (Platforms, Software, and AI as a Service), solution components (Hardware, Software, Services), management function (Automation, Planning and Logistics, Inventory Management, Fleet Management, Freight Brokerage, Risk Management, and Dispute Resolution), AI technologies (Cognitive Computing, Computer Vision, Context-aware Computing, Natural Language Processing, and

Machine Learning), and industry verticals (Aerospace, Automotive, Consumer Goods, Healthcare, Manufacturing, and others).

Donald et al. [36] (2003), said that inventory management is becoming increasingly important in today's growing economy. New products are continuously being developed and placed in the market for consumer purchase. This invention relates to inventory management systems and, more particularly, to methods and systems for performing an inventory management process that uses an intelligent station to track and/or inventory items that are tagged with Radio Frequency Identification (RFID) tags. The inventory management process may include at least one of an out of stock control process, a shrinkage recognition process, a rapid product recall process, an alert monitor process, and a sales optimization process. Each of these processes may perform various tasks that are used to manage the inventory of items in the environment, such as monitoring inventory levels of the items, detecting misplaced items in the environment, and providing feedback information associated with the items based on detected events (e.g., suggested alternative locations for certain items based on sales data).

Joseph et al. [37] (1999), demonstrated how an inventory management system automatically monitors inventory amounts, provides information concerning inventory, and decides if an order for replacement inventory should be placed. This invention is related to inventory management systems and methods. In particular, the invention is related to vendor-managed inventory systems and methods. The system and method provide information concerning inventory amounts and inventory ordering to a manufacturing site and an inventory vendor. The system comprises at least one storage receptacle that stores inventory; at least one amount indicator that determines an inventory amount in each receptacle, each amount indicator generating inventory amount signals representative of inventory amounts in the receptacle; at least one inventory price source that provides inventory price information; and a control unit that receives the inventory amount signals from the amount indicator and inventory price information from the inventory price source. The control unit analyzes the inventory amount signals to determine amounts in the receptacle. The control unit also analyzes the amounts and inventory price information, and uses this information to determine if an inventory order should be placed.

Yiwei et al. [38] (2011), developed a system, method and computer program product are made for demand modelling and prediction in retail categories. The method uses time-series data comprising of unit prices and unit sales for a designated choice set of related products, with the time-series data obtained over a given sequence of sales reporting periods, and over a collection of stores in a market geography. Other relevant data sets from participating retail entities that include additional product attribute data such as market and consumer factors that affect retail demand are further used. A demand model for improved accuracy is achieved by individual sub-modelling method steps of: estimating a model for price movements and price dynamics from the time series data of unit-prices in the aggregated sales data; estimating a model for market share of each product in the retail category using the aggregated sales data and integrated additional product attribute data; and, estimating generating a model for an overall market demand in the retail category from the aggregated sales data.

Akio et al. [39] (2006), proposed a system to support a purchase or a production of a product by accurately predicting a sold amount of the product. A system that supports a purchase or a production of a product, the system including an input section for accepting an input of a history of a supplied amount and a sold amount of the products, a function generating section for representing a conditional probability function showing probability distribution of a sold amount when the sold amount is restricted by the supplied amount by means of a potential demand probability function including a parameter showing probability distribution of the sold amount when it is supposed that the sold amount is not restricted by the supplied amount and computing a value of the parameter maximizing a value of a likelihood function of the conditional probability function using the input history as a sample to generate the potential demand probability function, and a supplied amount computing section for computing a supplied amount of the product maximizing a profit by a sale of the product, based on the generated potential demand probability function and a predetermined selling price and supplying price of the product, and outputting the amount as a quantity of the product to be purchased or produced.

Stephen et al. [40] (2000), said manufacturing firms are subject to pressure to do everything faster, cheaper, and better. Firms are expected to continue to improve customer service by increasing on-time deliveries and reducing delivery lead-times. At the same time, they must provide this service more cheaply and utilize fewer assets. Increasingly, firms need to do this for a global marketplace. The author develops a model for positioning safety stock in a supply chain. They model the supply chain as a network, where the nodes of the network are the stages of a supply chain. We assume that each stage uses a base-stock policy to control its inventory. They also assume that each stage quotes a service time to its customers, both internal and external, and that each stage provides 100% service for these quoted service times. Finally, they assume that external customer demand is bounded. They show how to evaluate the inventory requirements at each stage as a function of the service times. For supply chains that can be modelled as spanning trees, they develop an optimization algorithm for finding the service times that minimize the holding cost for the safety stock in the supply chain.

3.2. BACKGROUND

Most small-scale business shut down due to getting a very low or no return on investment. This happens due to unwanted expenditure and ill-maintained inventory. To overcome the money barrier for such businesses, a smart inventory management system is required which can ease the predicting part of investment in raw materials and give a clear visual of the growth of the business.

3.3. MOTIVATION

In the current scenario of economic recession, all new establishments require a way to streamline profit and to avoid low return on investment and have a successful business.

As a programmer point of view, the project helps understand a wide array of topics like K-nearest neighbour, predictive analysis and python libraries such as Keras, NumPy etc.

IV. METHODOLOGY

The problem is divided into two parts:
1. **Forecasting demand.**
2. **Calculating inventory variables.**

4.1. FORECASTING DEMAND:

Demand forecasting/prediction is the process of using historical data of orders to calculate future demand. To businesses, demand forecasting provides an estimate the amount of goods and services its customers will purchase in the foreseeable future.

The process is predicting demand can be divided into x steps:

- **Step 1: Collection of Historical Data**
  The first step for prediction is finding suitable data source for the problem. In our case, an inventory of medicines was taken into account. This dataset is sourced from Kaggle, an online dataset repository. It contains 8 medicines named - '#M01AB', '#M01AE', '#N02BA', '#N02BE', '#N05B', '#N05C', '#R03', '#R06'. Weekly order data is maintained in a CSV file. The format of the table is:

date	#M01AB	#M01AE	#N02BA	#N02BE	#N05B	#N05C	#R03	#R06

Column 1 – 'date' contains the date of the beginning of the week int the format 'MM-DD-YYYY'. The subsequent columns named after the medicines contain the weekly sale of the medicines. A sample screenshot of the dataset:

datum	# M01AB	# M01AE	# N02BA	# N02BE	# N05B	# N05C	# R03	# R06
1/5/2014	14	11.67	21.3	185.95	41	0	32	7
1/12/2014	29.33	12.68	37.9	190.7	88	5	21	7.2
1/19/2014	30.67	26.34	45.9	218.4	80	8	29	12
1/26/2014	34	32.37	31.5	179.6	80	8	23	10
2/2/2014	31.02	23.35	20.7	159.88	84	12	29	12

The dataset contains weekly orders from 01-05-2014 to 10-13-2019. Therefore, there are 248 entries in our dataset.

- **Step 2: Parsing the data**
  Since we are using Python as the Backend Language, parsing a CSV file to computer understandable format is done via a library called **Pandas.** The CSV file called "salesweekly.csv" is opened.

- **Step 3: Processing the data**
  CSV format is called a comma-delimited format. The CSV file when opened with a text formatting software looks like this:

```
Medicine,Given Lead Time,Actual Lead Time
#M01AB,7,7
#M01AB,7,6
```

For easy computation purpose, this comma-delimited data needs to be converted to a data structure to operate on it. The library **NumPy** comes into play here. This converts the data to an array which aids in the process of using the data to calculate results.

```
C:\Users\abhim\Desktop\AI_inventory_management>python inventory.py
[[14.   29.33 30.67 ... 39.01 36.68 25.02]
 [29.33 30.67 34.   ... 36.68 25.02 32.35]
 [30.67 34.   31.02 ... 25.02 32.35 39.36]
 ...
 [47.33 36.52 44.01 ... 40.71 35.51 46.84]
 [36.52 44.01 40.99 ... 35.51 46.84 34.01]
 [44.01 40.99 45.18 ... 46.84 34.01 38.7 ]]

C:\Users\abhim\Desktop\AI_inventory_management>python inventory.py
[32.35  39.36  25.69  19.68  36.03  27.36  26.36  22.02  24.67  22.38
 25.02  17.71  23.34  29.03  31.68  21.02  27.35  26.01  33.67  28.01
 20.02  28.36  26.02  36.36  22.05  29.7   18.7   18.02  25.36  32.35
 23.7   23.115 19.69  25.67  40.67  31.67  28.35  31.06  28.69  25.02
 25.01  36.18  36.68  19.34  39.35  29.69  32.19  20.34  35.01  21.67
 43.35  41.68  27.02  42.    25.01  35.01  40.18  41.65  36.66  29.34
 22.    35.    35.68  50.33  35.34  28.34  41.67  39.84  36.36  30.51
 38.71  36.35  50.36  33.83  41.01  41.17  51.68  39.35  38.33  38.67
 41.22  44.65  45.33  42.66  48.17  29.98  32.49  36.97  32.01  31.65
 31.32  41.51  32.99  31.98  33.33  41.65  51.67  27.98  46.01  51.66
```

- **Step 4: Choosing Prediction Algorithm**
  There are a number of Machine Learning based prediction models available to us. Some of these are K-Nearest Neighbours, Support Vector Machine (SVM), Linear Regression, Random Forest, etc. Each of these have their own advantages and disadvantages. There is no one-fits-all

algorithm for Prediction analysis, so we tested out a few until a suitable algorithm was found with decent accuracy. The python library used for the various machine learning prediction algorithms is **SKLearn.** For visualizing the results using graphs and plots we will use the **matplotlib** library.

Random Forest:

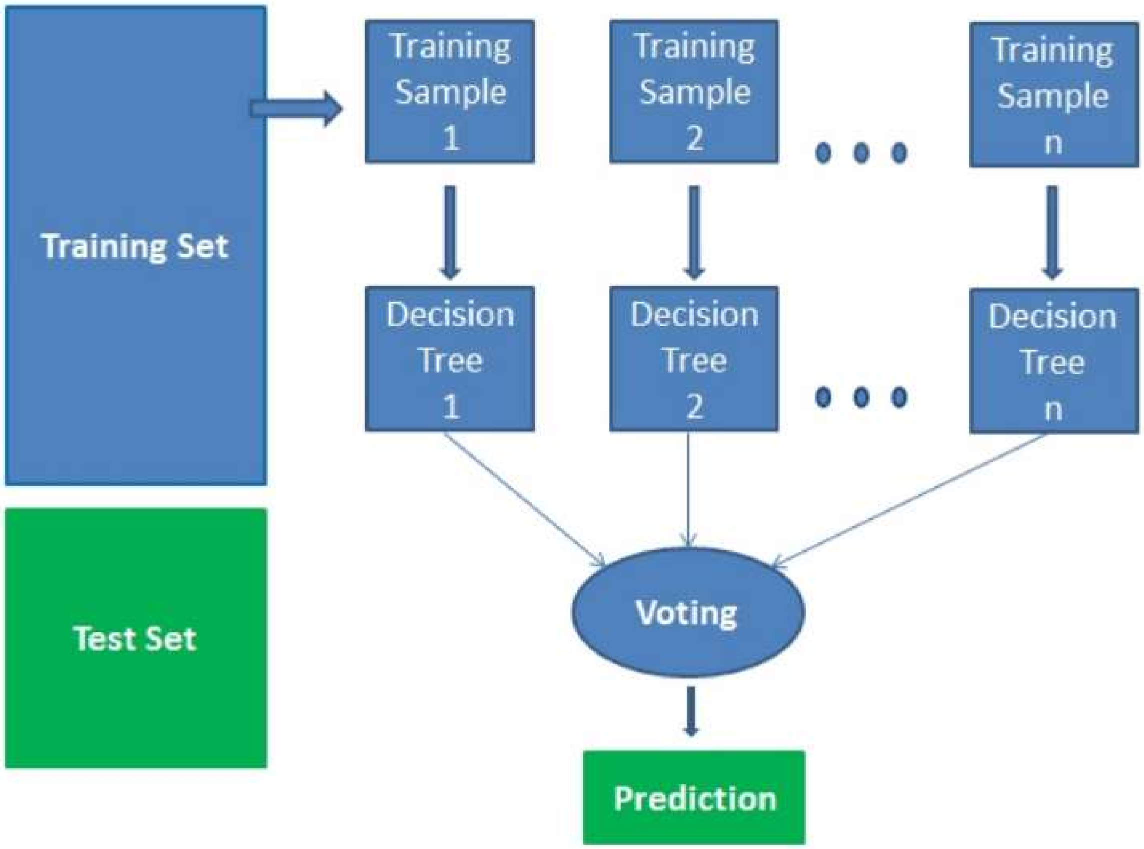
Random forest is a supervised learning algorithm. It can be used for both classification and regression. In our case we will use the random forest regressor. It creates decision trees on randomly selected data samples, gets prediction from each tree and selects the best solution by the means of voting. It works on four steps:

Step 1: Select random samples from a given dataset.
In our case the dataset is weekly orders of the past 10 weeks.

Step 2: Construct a decision tree for each sample and get a prediction result from each decision tree.

Step 3: Perform a vote for each predicted result.

Step 4: Select the prediction result with the most votes as the final prediction.



Decision trees are a popular method for various machine learning tasks. because it is invariant under scaling and various other transformations of feature values, is robust to inclusion of irrelevant features, and produces inspectable models. However, they are seldom accurate. In particular, trees that are grown very deep tend to learn highly irregular patterns:
they overfit their training sets, i.e. have low bias, but high variance. Random forests are a way of averaging multiple deep decision trees, trained on different parts of the same training set, with the goal of reducing the variance. This comes at the expense of a small increase in the bias and some loss of interpretability, but generally greatly boosts the performance in the final model.

Forests are like the pulling together of decision tree algorithm efforts. Taking the teamwork of many trees thus improving the performance of a single random tree.

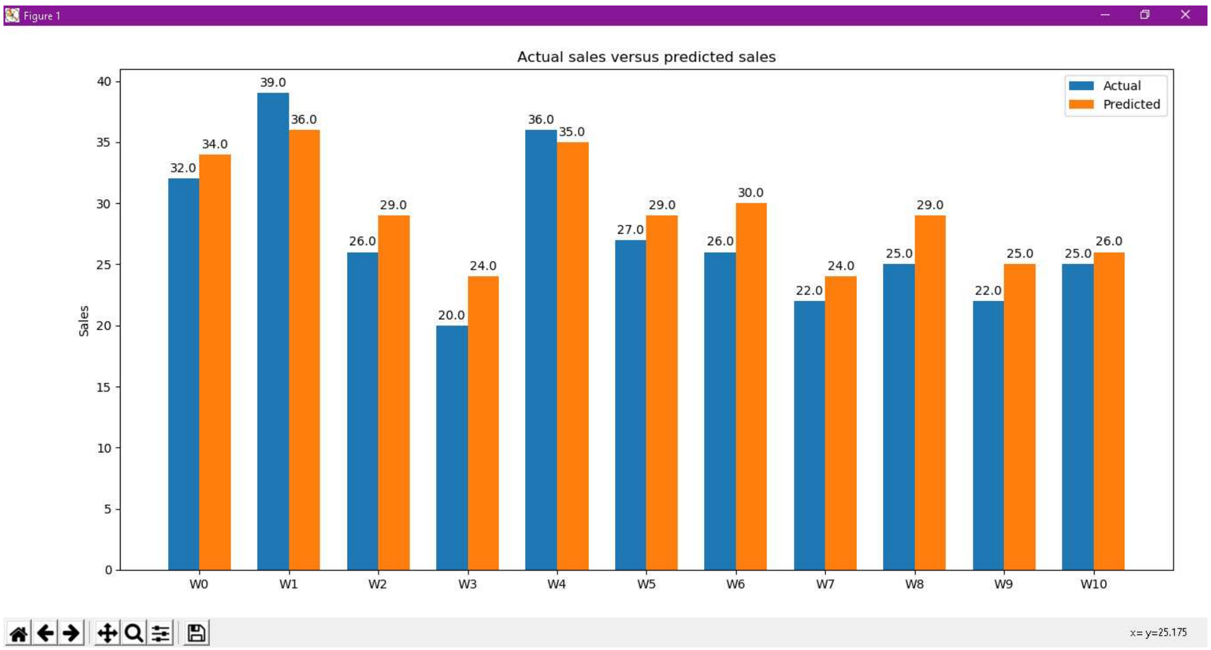
Random forests differ in only one way from this general scheme: they use a modified tree learning algorithm that selects, at each candidate split in the learning process, a random subset of the features. This process is sometimes called "feature bagging". The reason for doing this is the correlation of the trees in an ordinary bootstrap sample: if one or a few features are very strong predictors for the response variable (target output), these features will be selected in many of the *B* trees, causing them to become correlated.

Typically, for a classification problem with *p* features, $\sqrt{p}$ (rounded down) features are used in each split. For regression problems the inventors recommend *p/3* (rounded down) with a minimum node size of 5 as the default. In practice the best values for these parameters will depend on the problem, and they should be treated as tuning parameters.

Adding one further step of randomization yields extremely randomized trees, or ExtraTrees. While similar to ordinary random forests in that they are an ensemble of individual trees, there are two main differences: first, each tree is trained using the whole learning sample (rather than a bootstrap sample), and second, the top-down splitting in the tree learner is randomized. Instead of computing the locally optimal cut-point for each feature under consideration (based on, e.g., information gain or the Gini impurity), a random cut-point is selected. This value is selected from a uniform distribution within the feature's empirical range (in the tree's training set). Then, of all the randomly generated splits, the split that yields the highest score is chosen to split the node. Similar to ordinary random forests, the number of randomly selected features to be considered at each node can be specified. Default values for this parameter are $\sqrt{p}$ for classification and p for regression, where p is the number of features in the model.

The fine-tuning required in Random Forest regressor is the depth of the decision trees. It takes “max_depth” as a parameter to fix the depth of the tree. The deeper the tree, the more splits it has and it captures more information about the data. We fit each decision tree with different values of max_depth to find a suitable depth. The best accuracy of 82% was found with max_depth=10.

The algorithm has 2 variables: the independent variable and the dependent variable. The independent variable in our case is time, and the dependent variable is demand. We use 10 weeks of data to train the data. The 11^{th} week's data is used to test the model and the accuracy. Following is the plot for 10 random weeks demand forecasted vs the actual sales:



The accuracy calculated was 82% which gave us an error limit of ±5 units of medicine. This was in our acceptable range and thus this algorithm is selected as our final algorithm.

- **Step 5: Predicting future demand**
  With the selection of a fitting algorithm and testing we can now move on with the prediction. The following data is predicted for the subsequent weeks:

```
C:\Users\abhim\Desktop\AI_inventory_management>python inventory.py
[34.00881486 35.83640627 29.4546001  24.01534105 34.75151045 29.00657496
 30.0599914  24.36764229 28.89136523 24.91321725 26.10184829 23.22691424
 25.00578764 27.02033211 30.15500952 22.43013257 26.15746571 27.02626882
 31.89574488 28.81225189 22.97371849 28.10296608 27.51255423 32.60143568
 24.49914295 30.50002924 22.81872967 22.43387465 26.29009638 32.02255183
 26.02964388 24.69086715 21.64322563 27.16142139 34.71108947 30.04237232
 29.3388616  29.3059182  27.924086   27.4607474  27.37643261 35.2199463
 34.75576282 25.10921121 35.33843211 29.7959232  35.48632805 23.7496016
 33.64064613 25.00801963 39.5684789  37.98219563 30.2232174  38.4693904
 26.16916714 36.19961613 35.89850932 39.66584334 35.36573923 31.37292605
 29.62146933 34.32593947 34.69913058 43.86029761 34.74374055 33.17965922
 40.41477968 36.43394827 36.63869039 33.40145889 38.63068054 35.22908379
 46.86460711 35.47821626 38.406743   38.8884083  45.57354942 37.19039402
 38.80374652 38.82200538 40.50504262 42.0911067  41.74154928 39.75552925
 43.02547825 36.87444097 36.62218396 36.45855361 33.98135927 33.66681916
 33.30759072 37.67845387 34.17739374 35.39120062 35.07235224 38.18361172
 41.28427962 32.58153041 41.14515539 44.80442932]
```

4.2. <u>CALCULATING INVENTORY VARIABLES:</u>

A smart inventory management system not only predicts the demand but also fine tunes the stock and reordering process to streamline profit in the business.

The different variables in Supply Chain Management are:

- Safety Stock: It is the extra stock that is maintained to mitigate the risk of stockouts, i.e. shortage in raw material, caused by uncertainties in supply and demand. Adequate safety stock levels permit business operations to proceed according to plan.
- Reorder Quantity: At the time of reordering an amount needs to be decided to strike a balance between two factors: having enough stock to sustain the business and mitigate risks and not having surplus stock that leads to unusable principal and also increases cost of inventory.
- Lead Time: The time taken between ordering of raw material and it reaching the inventory.

These two factors when calculated correctly can decrease the risk of failure of business by eternal factors and also maintaining enough inventory that the cost of sustenance is low and in case of failure, the loss isn't huge.

- **Step 1: Calculating statistics functions on Lead Time and Sales**

The lead time is contained in a CSV file called 'lead_time.csv'. This is parsed using **Pandas** library. The design of the file is as follows:

Medicine	Given Lead Time	Actual Lead Time

A sample entry in the dataset is as follows:

Medicine	Given Leac	Actual Lead Time
#M01AB	1	0.857143
#M01AB	1	0.857143
#M01AB	1	1.285714

The Given and Actual Lead time are in weeks calculated as number of days/7. Mean and standard deviation on Actual Lead time is calculated by Pandas function '.mean()' and '.std()'. Using the 10 weeks dataset part 1 of the problem, average sales and standard deviation of sales is calculated.

- **Step 2: Calculating z-score in Normal Distribution**
  We've determined our desired service level to be 90%.
  The z value for a number of samples is given by the equation:

$$z_i = \frac{x_i - \bar{x}}{S}$$

Where,
x_i = value of ith sample
$\bar{x}$ = mean of sample
S = standard deviation of sample
Averaging out this equation for the data present in our dataset, we obtain a z value of 1.2816.
This z value can also be confirmed from the following table for a 90% level of confidence. Therefore, we take the z value as 1.28.

Service Level	Service Factor	Service Level	Service Factor
50.00%	00.00	90.00%	01.28
55.00%	00.13	91.00%	01.34
60.00%	00.25	92.00%	01.41
65.00%	00.39	93.00%	01.48
70.00%	00.52	94.00%	01.55
75.00%	00.67	95.00%	01.64
80.00%	00.84	96.00%	01.75
81.00%	00.88	97.00%	01.88
82.00%	00.92	98.00%	02.05
83.00%	00.95	99.00%	02.33
84.00%	00.99	99.50%	02.58
85.00%	01.04	99.60%	02.65
86.00%	01.08	99.70%	02.75
87.00%	01.13	99.80%	02.88
88.00%	01.17	99.90%	03.09
89.00%	01.23	99.99%	03.72

- **Step 3: Calculating Safety Stock**
  Safety stock will be calculated with the following formula:
  $$Safety\ Stock = \left(Z * std(sales) * \sqrt{mean(LT)}\right) + (Z * mean(sales) * std(LT))$$
  Where,
  Z = Z-Score based on Service Level (1.28)
  std(x) = Standard Deviation of x
  mean(x) = Mean of x
  sales = sale of the previous 10 weeks
  LT = Lead Time

  This is using a normal distribution with uncertainty on demand and dependent lead time. For situations where demand and lead time are linked, we consider using this formula. It could be that lead time causes uncertainty on demand or that demand is having an impact on lead times. Because variability can impact sales and vice versa, typically more safety stock is needed to account for these unpredictable variations.

  Quantity of Reorder will be calculated using the following formula:

$$QOR = Demand + \left(\left(1 - {}^{accuracy}/_{100}\right) * Demand\right) + Safety\ Stock$$

Where,

QOR = Quantity of Reorder
Demand = Predicted demand of the next week using Random Forest Algorithm
Accuracy = Accuracy of model calculated during Testing
Safety Stock = Safety Stock calculated in last step

With Demand, Safety Stock and Quantity of Reorder calculated we have achieved our objectives.

V. PLATFORM

5.1. BACKEND

CSV files called ‘sales_weekly.csv’, for sales data to train the model and test it is used, and ‘lead_time.csv’, for lead time data for safety stock calculation is used.

Python libraries are used to process and calculate the results:

- Pandas: To read and parse the CSV file
- NumPy: To convert CSV data to Array form for easy processing
- Math: To calculate the statistical variables
- Matplotlib: To visualize the data using graphs and plots
- SKLearn: To implement Machine Learning Prediction Algorithms like Random Forest, Linear Regression etc.

5.2. FRONTEND

The platform used to execute the system is **CMD** and the language used for writing the script for the system is **Python3.**

VI. SAMPLE CODING

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import pickle
from sklearn import svm
from sklearn.ensemble import RandomForestRegressor

#Array Creation for med1
x1 = list()
y1 = list()
for i in range(len(med1)-10):
    x = np.array(med1.loc[i:i+9])
    y = np.array(med1.loc[i+10])
    x1.append(x)
    y1.append(y)
x1 = np.array(x1).reshape(292,10)
y1 = np.array(y1).reshape(292,)

#Random Forests 85%
reg = RandomForestRegressor(max_depth=10,random_state=10)
reg.fit(x1,y1)
print(reg.score(x1,y1))
p = reg.predict(x1)

#Save model1
filename = 'model1.sav'
pickle.dump(reg, open(filename, 'wb'))
model1 = pickle.load(open(filename, 'rb'))

#Read data from table
data = pd.read_csv("salesweekly.csv")
data.drop(0)
data.drop("datum",axis=1,inplace=True)
med1 = data[["M01AB"]]
med2 = data[["M01AE"]]
med3 = data[["N02BA"]]
med4 = data[["N02BE"]]
med5 = data[["N05B"]]
med6 = data[["N05C"]]
med7 = data[["R03"]]
med8 = data[["R06"]]

#---------------------------------------------------------------------------
```

```
#Take inputs
product = ['#M01AB', '#M01AE', '#N02BA', '#N02BE', '#N05B', '#N05C', '#R03
', '#R06']
df = pd.read_csv(r'lead_time.csv', index_col=0)
index = int(input("Enter index="))
print("Enter sales")
currentsales = float(input())
print("Finding data for "+product[index]+"....")

#--------------------------------------------------------------------------

#Choose model based on index
if index == 0:
    x = np.array(med1.loc[len(med1)-9:])
    x = np.append(x,currentsales).reshape(1,10)
    filename = 'model1.sav'
    accuracy = 0.82

if index == 1:
    x = np.array(med2.loc[len(med2)-9:])
    x = np.append(x,currentsales).reshape(1,10)
    filename = 'model2.sav'
    accuracy = 0.77

if index == 2:
    x = np.array(med3.loc[len(med3)-9:])
    x = np.append(x,currentsales).reshape(1,10)
    filename = 'model3.sav'
    accuracy = 0.86

if index == 3:
    x = np.array(med4.loc[len(med4)-9:])
    x = np.append(x,currentsales).reshape(1,10)
    filename = 'model4.sav'
    accuracy = 0.94

if index == 4:
    x = np.array(med5.loc[len(med5)-9:])
    x = np.append(x,currentsales).reshape(1,10)
    filename = 'model5.sav'
    accuracy = 0.86

if index == 5:
    x = np.array(med6.loc[len(med6)-9:])
    x = np.append(x,currentsales).reshape(1,10)
```

```
    filename = 'model6.sav'
    accuracy = 0.77

if index == 6:
    x = np.array(med7.loc[len(med7)-9:])
    x = np.append(x,currentsales).reshape(1,10)
    filename = 'model7.sav'
    accuracy = 0.87

if index == 7:
    x = np.array(med8.loc[len(med8)-9:])
    x = np.append(x,currentsales).reshape(1,10)
    filename = 'model8.sav'
    accuracy = 0.93

#---------------------------------------------------------------------------

#Calculate Demand
model = pickle.load(open(filename, 'rb'))
demand = model.predict(x)
print("The predicted demand is: ")
print(demand[0])
mean1 = np.mean(x)
std1 = np.std(x)

#Inventory
def lt_mean(index):
    #print(df['Actual Lead Time'][str(product[index])])
    return df['Actual Lead Time'][str(product[index])].mean()

def lt_std(index):
    return df['Actual Lead Time'][str(product[index])].std()

def ss_cal(z,prod_mean,prod_std,mean1,std1):
    ss = (z*std1*np.sqrt(prod_mean))+(z*mean1*prod_std)
    return ss

def qor_cal(demand, accuracy, ss):
    qor = demand+((1-accuracy)*demand)+ss
    return qor

prod_mean=lt_mean(index)
prod_std=lt_std(index)

z=1.28
```

```python
safety_stock= np.ceil(ss_cal(z,prod_mean,prod_std,mean1,std1))
print("Required Safety Stock=")
print(safety_stock)

qor = np.ceil(qor_cal(demand, accuracy, safety_stock))
print("Required Quantity of Reorder=")
print(qor[0])
```

VII. RESULT

7.1. TEST CASE 1

Input:

Index = 0
Sales = 30

Output:

Predicted demand = 34.7932
Required Safety Stock = 24.0
Required Quantity of Reorder = 66.0

7.2. TEST CASE 2

Input:

Index = 1
Sales = 20

Output:

Predicted demand = 24.7989
Required Safety Stock = 16.0
Required Quantity of Reorder = 47.0

VIII. DISCUSSION

Safety stock refers to the minimum amount of inventory the person should have available at all times. This is to compensate for any sudden demands and to ensure that the needs of all clients are met.

The quantity of reorder refers to the amount of inventory the person needs to reorder. It is based on the demand predicted and its accuracy.

If the inventory falls below the safety stock, inventory should automatically be reordered.

$$Safety\ Stock = \left(Z * std(sales) * \sqrt{mean(LT)}\right)$$
$$+(Z * mean(sales) * std(LT))$$

For the first test case, we have:
Z = 1.28
std(sales) = 10.63
mean (LT) = 1.057
mean(sales) = 35.085
std (LT) = 0.204

From this we can see that safety stock is:
SS = (1.28 * $\sqrt{1.057}$) + (1.28 * 35.085 * 0.204)
Therefore, the safety stock will be 24.

$$QOR = Demand + \left(\left(1 - {}^{accuracy}/_{100}\right) * Demand\right) + Safety\ Stock$$

Demand = 34.793
Accuracy = 82%
Safety Stock = 24
QOR = 34.793 + ((1-0.82) *34.793) + 24
Therefore, the Quantity of Reorder will be 66.

IX. CONCLUSION & FUTURE SCOPE

In this project, we succeeded in predicting the demand of 8 different products based on 10 weeks' worth of sales. With the help of this demand, we were also able to calculate the safety stock as well as the quantity that needs to be reordered. In the future, we can make significant improvements in this system by adding an interface to make it easier to work with. We can also make improvements with regards to the accuracy of the machine learning models as and when more data is obtained.

ITE2010 – ARTIFICIAL INTELLIGENCE

REVIEW – 3

TOPIC: SMART INVENTORY MANAGEMENT SYSTEM

Team:

1. Abhimanyu Singh - 18BIT0105
2. Nitin Sharma – 18BIT0145

Slot: B2

Submitted to: Prof. Ajit Kumar Santra

I. ABSTRACT

The Smart Inventory Management System predicts the demand of a particular product and allows the user to see the future growth as well as analyse how much raw material is required to be ordered/purchased for the same. The daily demand of 1 year is taken into account to populate the dataset and daily demand is predicted using a python script.

Demand can be represented using plots and can also be computed numerically. This can be beneficial as no extra money will be wasted on raw materials and also can free up the inventory.

II. OBJECTIVES

- To predict daily demand
- To compute amount of raw material to be ordered

III. INTRODUCTION

Small Scale Industries (SSIs) account for nearly 55% of the total industries in our country. Most of these are rural population owned where principal amount to start such business is low. So, to streamline the expenditure and stabilize the profit and investment ratio, we can use a smart inventory management system. The model uses machine learning to extract the dataset populated with the daily demand of the products in the inventory and process it with predictive analysis to compute the predicted growth of the demand.

3.1. LITERATURE REVIEW

Du et al. [1] (2019), stated that research interests in machine learning (ML) and supply chain management (SCM) have yielded an enormous amount of publications during the last two decades. The aim of this study is to provide a comprehensive view of ML applications in SCM, working as a reference for future research directions for SCM researchers and application insight for SCM practitioners. ML is a subbranch of AI that equips the machines with the capability to automatically learn from the data existing with no specific programming. Based on the learning methods, the research design is classified into supervised learning, unsupervised learning and reinforcement learning. The research finds that the most frequently used research design is supervised learning (87%), followed by unsupervised learning (8%) and reinforcement learning (5%). It is worth noting that only 10 out of 32 commonly recognized ML algorithms have been frequently applied in SCM. The 10 most commonly used algorithms identified were Decision Trees, Random Forest, K-means, K-Nearest Neighbor, Logistic Regression, Naïve Bayes, Neural Networks, Support Vector Machine, Ensemble Algorithms and Extreme Learning Machines. Out of these, the most commonly used algorithms were Neural Networks (54%) and Support Vector Machines (22%). These algorithms are used in 6 major areas which have been identified as Demand/sales estimation, Procurement and supply management, Production, Transportation and distribution, Inventory and storage and Supply chain improvement.

Pawet [2] (2016), presents a proposal for a combined application of fuzzy logic and genetic algorithms to control the procurement process in the enterprise. The approach presented in this paper draws particular attention to the impact of external random factors in the form of demand and lead time uncertainty. The model uses time-variable membership function parameters in a dynamic fashion to describe the modelled output fuzzy (sets) values. An additional element is the use of genetic algorithms for optimization of fuzzy rule base in the proposed method. The approach presented in this paper was verified according to four criteria based on a computer simulation performed on the basis of the actual data from an enterprise.

Tereza [3] (2016), said that to examine suitable methods of artificial neural networks and their application in business operations, specifically to the supply chain management. The article discusses construction of an artificial neural networks model that can be used to facilitate optimization of inventory level and thus improve the ordering system and inventory management. For the data analysis from the area of wholesale trade with connecting material is used. Methods used in the paper consists especially of artificial neural networks and ANN-based modelling. For data analysis and preprocessing, MS Office Excel software is used. As an instrument for neural network forecasting MathWorks MATLAB Neural Network Tool was used. Deductive quantitative methods for research are also used. The effort is directed at finding whether the method of prediction using artificial neural networks is suitable as a tool for enhancing the ordering system of an enterprise. The research also focuses on finding what architecture of the artificial neural networks model is the most suitable for subsequent prediction. Artificial neural networks models can be used for inventory management and lot-sizing problem successfully. A network with the TRAINGDX training function and TANSIG transfer function and 6-8-1 architecture can be considered the most suitable for artificial neural network, as it shows the best results for subsequent prediction. It can be concluded that the created model of artificial neural network can be successfully used for predicting order size and therefore for improving the order cycle of an enterprise.

Bo [4] (2010), demonstrated that product take-back legislation forces manufacturers to bear the costs of collection and disposal of products that have reached the end of their useful lives. In order to reduce these costs, manufacturers can consider reuse, remanufacturing and/or recycling of components as an alternative to disposal. The implementation of such alternatives usually requires an appropriate reverse supply chain management. With the concepts of reverse supply chain gaining popularity in practice, the use of artificial intelligence approaches in these areas is also becoming popular. As a result, the purpose of this paper is to give an overview of the recent publications concerning the application of artificial intelligence techniques to reverse supply chain with emphasis on certain types of product returns.

Resul et al. [5] (2020), stated that supply and demand are two fundamental concepts of sellers and customers. Predicting demand accurately is critical for organizations in order to be able to make plans. In this paper, the authors propose a new approach for demand prediction on an e-commerce web site. The proposed model differs from earlier models in several ways. The business model used in the e-commerce web site, for which the model is implemented, includes many sellers that sell the same product at the same time at different prices where the company operates a market place model.

The demand prediction for such a model should consider the price of the same product sold by competing sellers along the features of these sellers. In this study the authors first applied different regression algorithms for a specific set of products of one department of a company that is one of the most popular online e-commerce companies in Turkey. Then they used stacked generalization also known as stacking ensemble learning to predict demand. Finally, all the approaches were evaluated on a real-world data set obtained from the e-commerce company. The experimental results show that some of the machine learning methods do produce almost as good results as the stacked generalization method.

Benjamin [6] (1997), discusses an application of neuro-dynamic programming techniques for the optimization of retailer inventory systems. It describes a specific case study involving a model with thirty-three states. The enormity of this state space renders classical algorithms of dynamic programming inapplicable. The performance of solutions generated by neuro-dynamic programming algorithms are compared to that delivered by optimized s-type ("order-up-to") policies. The study enables the generation of substantially superior control strategies which helps in reducing inventory costs by approximately ten percent.

George [7] (2019), showed supply chain risk management (SCRM) encompasses a wide variety of strategies aiming to identify, assess, mitigate and monitor unexpected events or conditions which might have an impact, mostly adverse, on any part of a supply chain. SCRM strategies often depend on rapid and adaptive decision-making based on potentially large, multidimensional data sources. These characteristics make SCRM a suitable application area for artificial intelligence (AI) techniques. The aim of this paper is to provide a comprehensive review of supply chain literature that addresses problems relevant to SCRM using approaches that fall within the AI spectrum. To that end, an investigation is conducted on the various definitions and classifications of supply chain risk and related notions such as uncertainty. Then, a mapping study is performed to categorize existing literature according to the AI methodology used, ranging from mathematical programming to Machine Learning and Big Data Analytics, and the specific SCRM task they address (identification, assessment or response). Finally, a comprehensive analysis of each category is provided to identify missing aspects and unexplored areas and propose directions for future research at the confluence of SCRM and AI.

Gérard et al. [8] (2000), stated that in traditional supply chain inventory management, orders are the only information firms exchange, but information technology now allows firms to share demand and inventory data quickly and inexpensively. The study assesses the value of sharing these data in a model with one supplier, N identical retailers, and stationary stochastic consumer demand. There are inventory holding costs and back-order penalty costs. The study compares a traditional information policy that does not use shared information with a full information policy that does exploit shared information. In a numerical study it is found that supply chain costs are 2.2% lower on average with the full information policy than with the traditional information policy, and the maximum difference is 12.1%. A simulation-based lower bound over all feasible policies is also developed. The cost difference between the traditional information policy and the lower bound is an upper bound on the value of information sharing: In the same study, that difference is 3.4% on average, and no more than 13.8%. The study contrasts the value of information sharing with two other benefits of information technology, faster and cheaper order processing, which lead to shorter lead times and smaller batch sizes, respectively. In the sample, cutting lead times nearly in half reduces costs by 21% on average, and cutting batches in half reduces costs by 22% on average. For the settings studies, it is concluded that implementing information technology to accelerate and smooth the physical flow of goods through a supply chain is significantly more valuable than using information technology to expand the flow of information.

Jin et al. [9] (2016), demonstrated that with the emergence of individualized and personalized customer demands, the interaction of service and product has come into the sight of manufacturers and thus promoted the arising of service-oriented manufacturing (SOM), a new business mode that combines manufacturing and service. Similar to the conventional manufacturing, the customer demand prediction (CDP) of SOM is very important since it is the foundation of the following manufacturing stages. As there are always tight and frequent interactions between service providers and customers in SOM, the customer satisfaction would significantly influence the customer demand of the following purchasing periods. To cope with this issue, a novel CDP approach for SOM incorporating customer satisfaction is proposed. Firstly, the structural relationships among customer satisfaction index and the influence factors are quantitatively modelled by using the structural equation model. Secondly, to reduce the adverse effect of multiple structural input data and small sample size, the least square support vector mechanism is employed to predict customer demand. Finally, the CDP of the air conditioner compressor which is a typical SOM product is implemented as the real-case example, and the effectiveness and validity of the proposed approach is elaborated from the prediction results analysis and comparison.

Xin et al. [10] (2004), published that traditional inventory models focus on risk-neutral decision makers, i.e., characterizing replenishment strategies that maximize expected total profit, or equivalently, minimize expected total cost over a planning horizon. The study proposes a framework for incorporating risk aversion in multiperiod inventory models as well as multiperiod models that coordinate inventory and pricing strategies. It shows that the structure of the optimal policy for a decision maker with exponential utility functions is almost identical to the structure of the optimal risk-neutral inventory (and pricing) policies. These structural results are extended to models in which the decision maker has access to a (partially) complete financial market and can hedge its operational risk through trading financial securities. Computational results demonstrate that the optimal policy is relatively insensitive to small changes in the decision-maker's level of risk aversion.

Ilaria et al. [11] (2002), stated that a major issue in supply chain inventory management is the coordination of inventory policies adopted by different supply chain actors, such as suppliers, manufacturers, distributors, so as to smooth material flow and minimize costs while responsively meeting customer demand. This paper presents an approach to manage inventory decisions at all stages of the supply chain in an integrated manner. It allows an inventory order policy to be determined, which is aimed at optimizing the performance of the whole supply chain. The approach consists of three techniques: (i) Markov decision processes (MDP) and (ii) an artificial intelligent algorithm to solve MDPs, which is based on (iii) simulation modeling. In particular, the inventory problem is modeled as an MDP and a reinforcement learning (RL) algorithm is used to determine a near optimal inventory policy under an average reward criterion. RL is a simulation-based stochastic technique that proves very efficient particularly when the MDP size is large.

Kochak et al. [12] (2015), showed that the demand forecasting technique which is modelled by artificial intelligence approaches using artificial neural networks. The consumer product causers the difficulty in forecasting the future demand and the accuracy of the forecast in performance of the artificial neural network an advantage in a constantly changing business environment and demand forecasting an organization in order to make right decisions regarding manufacturing and inventory management. The learning algorithm of the prediction is also imposed to better prediction of time series in future. The prediction performance of recurrent neural networks a simulated time series data and a practical sales data have been used. This is because of influence of several factors on demand function in retail trading system. It was also observed that as forecasting period becomes smaller, the ANN approach provides more accuracy in forecast.

Jing et al. [13] (2013), introduced the characteristics and basic application of RFID technology, analyses the data flow of intelligent inventory system from the perspective of business and function, then puts forward the specific framework programs and function modules of intelligent inventory management system based on IOT RFID technology, focuses on elaborating the design and implementation process of the intelligent inventory system. The system realizes full control and management of all products, faster in/out warehouse and dynamic inventory, utilizes warehouse efficiently and improves the capacity of warehouse by effective combining with the ERP system in enterprise.

Lipshutz et al. [14] (1991), showed that the Logistics Inventory Management System is an expert system to assist Unisya spare parts inventory analysts in developing an action plan on a part by part basis to maintain inventory levels within a target zone. The task is complex and has significant cost impact. LIMA is a PC-hosted tool, incorporating business presentation graphics, statistical analysis, “what if ... “capabilities and expert assistance from a Prolog knowledge base. Data provided to LIMA are extracted from a large mainframe database of parts usage. The expert system component guides the analyst through a data validation process, generates an action plan to cover the planning period and engages the analyst in a planning dialogue.

Hokey [15] (2010), published that artificial intelligence (AI) was introduced to develop and create “thinking machines” that are capable of mimicking, learning, and replacing human intelligence. Since the late 1970s, AI has shown great promise in improving human decision-making processes and the subsequent productivity in various business endeavours due to its ability to recognize business patterns, learn business phenomena, seek information, and analyze data intelligently. Despite its widespread acceptance as a decision-aid tool, AI has seen limited application in supply chain management (SCM). To fully exploit the potential benefits of AI for SCM, this paper explores various sub-fields of AI that are most suitable for solving practical problems relevant to SCM. In so doing, this paper reviews the past record of success in AI applications to SCM and identifies the most fruitful areas of SCM in which to apply AI.

Yashoda [16] (2018), demonstrated that with accumulation and proliferation of large data, it is highly necessary to make some meaningful sense out of the data. Here is where Artificial Intelligence (AI) tools and algorithms play a major role. AI is highly expertise in handling the customer data and forecasting the purchase behavior of customers. This has brought out the biggest level of automation in the ecommerce industry. AI provide notification when a company has to re-order stock and assist in creating manufacturing schedule as per the variation in demand during the particular period of time accurately. The autonomous and data-driven supply chain has optimized logistics, manufacturing, warehousing and the last mile delivery. E-commerce giant like Amazon use leads to time and forecasting techniques to critically plan inventory orders. Machine learning system (MLS), a subset of AI solves the cognitive problems associated with human intelligence and helps to optimize logistic speed and quality. This paper discusses AI-based inventory management tools which are being utilized in the e-commerce industry. AI provides customers an enriched experience which helps to maximize profits.

Woschank et al. [17] (2020), showed that industry 4.0 concepts and technologies ensure the ongoing development of micro and macro-economic entities by focusing on the principles of interconnectivity, digitalization, and automation. In this context, artificial intelligence is seen as one of the major enablers for Smart Logistics and Smart Production initiatives. This paper systematically analyzes the scientific literature on artificial intelligence, machine learning, and deep learning in the context of Smart Logistics management in industrial enterprises. Furthermore, based on the results of the systematic literature review, the authors present a conceptual framework, which provides fruitful implications based on recent research findings and insights to be used for directing and starting future research initiatives in the field of artificial intelligence (AI), machine learning (ML), and deep learning (DL) in Smart Logistics.

Boru et al. [18] (2019), showed in this paper, a new hybrid method including simulation optimization and artificial intelligence-based simulation is created to solve the inventory routing problem (IRP) in which three different routing strategies are evaluated for uneven demand patterns including intermittent, erratic, and lumpy demand. The proposed method includes two phases. In the first phase, a nondominated sorting genetic algorithm II-based simulation is employed to perform a multi-objective search for the IRP where the objectives of the method are total supply chain cost minimization and average service level maximization. In the second phase, artificial neural network-based simulation is used to adjust the reorder point and order-up-to-level by forecasting the customer demand at each replenishment time. The results of the study demonstrated that the average service level is at least 98.54% in the supply chain. From this, it can be concluded that the proposed method can provide a tremendous opportunity to improve the average service level under uncertain environments. In addition, it is determined that different routing strategies can be selected for different demand patterns according to the considered performance measures.

Praveen et al. [19] (2020), showed that a major requirement for small/medium-sized businesses is Inventory Management since a lot of money and skilled labor has to be invested to do so. E-commerce giants use Machine Learning models to maintain their inventory based on demand for a particular item. Inventory Management can be extended as a service to small/medium sized businesses to improve their sales and predict the demand of various products. Demand forecasting is a crucial part of all businesses and brings up the following question: How much stock of an item should a company/business keep to meet the demands, i.e., what should the predicted demand of a product be? Among its many benefits, a predictive forecast is a key enabler for a better customer experience through the reduction of out-of-stock situations, and for lower costs due to better planned inventory and less write-off items. The paper discusses the challenges of building an Inventory system and discusses the design decisions.

Min-Chun [20] (2011), published that ABC analysis is a popular and effective method used to classify inventory items into specific categories that can be managed and controlled separately. Conventional ABC analysis classifies inventory items three categories: A, B, or C based on annual dollar usage of an inventory item. Multi-criteria inventory classification has been proposed by a number of researchers in order to take other important criteria into consideration. These researchers have compared artificial-intelligence (AI)-based classification techniques with traditional multiple discriminant analysis (MDA). Examples of these AI-based techniques include support vector machines (SVMs), backpropagation networks (BPNs), and the *k*-nearest neighbours (*k*-NN) algorithm. To test the effectiveness of these techniques, classification results based on four benchmark techniques are compared. The results show that AI-based techniques demonstrate superior accuracy to MDA. Statistical analysis reveals that SVM enables more accurate classification than other AI-based techniques. This finding suggests the possibility of implementing AI-based techniques for multi-criteria ABC analysis in enterprise resource planning (ERP) systems.

Muhammad et al. [21] (2015), showed that Enterprise Resource Planning (ERP) systems provides function to calculate Safety Stock (SS), demand forecast and determine Reorder Point (ROP) for each product in the stock. The earlier used systems lack proper accuracy for slow moving items like spare products. The proposed model uses pooled distribution, instead of Poisson distribution, according to similarities in the demand history and lead times of spare products. This is more feasible and practical alternative to complex theoretical distributions. The advantage of this model is it is easier to implement and integrate with the existing ERP systems compared to other frequently used models. The disadvantage of the said model is with time, the group probability distribution of the spare items must be calculated periodically. Also, obsolescence cost and variable lead time aren't taken into account in the model.

Woschank et al. [22] (2020), wrote in this paper that smart logistics aims at the successful implementation of intelligent and lean supple chains based on agile and cooperative networks and interlinked organizations. This paper conducts a systematic literature review of recent studies regarding the application of ML, AI and DL in smart logistics. It is found that the technology is still in its early stages. Most of the developments are conceptual and in early testing phase. The technologies found were Strategic and Tactical Process Optimization, Cyber-Physical Systems, Predictive maintenance, Hybrid decision support systems, production planning and control systems and intelligent transport logistics. These topics lack mature industrial applications. Therefore, for further development other fields such as IT, logistics, mechanical engineering, statistics, etc. must be integrated.

Hanson et al. [23] (2019), published that Big data is the usage of the vast structured and unstructured data generated by a system. AI is the use of computers to execute decisions which are "smart" in nature, i.e. self-made decision based on some pattern or algorithm. Big data is used by industries to collect the enterprise data from all the ERP systems, verify and clean it. AI is used in Supply Chain Management to forecast demand, develop new business models and identification of radical customization of services. It is concluded that to achieve and retain customer confidence and trust, organizations that use AI and Big data need to be able to present the authenticity of the data generated. Effective use of AI and big data presents opportunities to organizations to develop the business to be human-free and also be according to the customer market.

Pervaiz [24] (2020), showed how the man-made reasoning or AI is functioning in the Supply Chain Management. It is found that AI is very much integrated with the systems related to SCM. The use of chat-bots to automate replies is quite common. Smart warehouses are used to automate the inventory management which leads to increased revenue. Genetic algorithms are used to improve delivery times and reducing costs by finding the shortest paths. It is concluded that AI has brought about a major change in the industry which has led to an increased efficiency.

Toktay et al. [25] (2000), demonstrated that remanufacturing is the process of using products which are recovered, processed and sold as new products. The proposed model is used to develop a supply chain for Kodak's single-use camera, from the overseas production of circuit boards to the photofinishing lab's development of the film and subsequent return to the camera factory. Queueing network is used to model production and distribute facilities whereas, statistical aspects of problem are dynamically estimated like the probability that sold cameras are returned, delay of returned cameras etc. The model lacks the usage of customer demand i.e. seasonal demand and unsatisfied demand are unaccounted which leads to a doubt on the overall efficacy of the proposed system to solve a real-world problem.

Yashoda [26] (2018), showed that e-commerce involves buying and selling of goods on the internet platforms. Other than money transactions, timely transportation of goods is required too. This calls for a smart supply chain. Big companies in E-commerce like Flipkart and Amazon are expanding their horizons with the use of AI. Amazon uses it to predict customer behavior and required inventory. Machine learning is used to analyze market campaigns and predict inventory. Amazon Machine Learning Algorithm has reduced the complexities of traditional forecasting models and has provided better speeds and accuracy. Overall, AI has revolutionized the e-commerce sector with its high accuracy and real time analysis. This has led to better understanding of customer patterns and increased the profits.

Michalski [27] (2008), demonstrated how traditional inventory management models work at providing a basic aim of every business: maximize its profit. The proposed model helps achieve one more aim along with the existing ones: maximize the value of the business. The paper provides modifications to both the value-based EOQ (Economic Order Quantity) model and value-based POQ (Production Order Quantity) model. The aim of this model is to find a balance between keeping high inventory to increase profits by sales but also increasing the risk, and keeping excess cash in inventory. The proposed model by bringing this balance makes for better value-based decisions for the firm.

Matthew et al. [28] (2013), stated Data Science, predictive analytics and big data, the confluence of them commonly called BDP is the up and coming trend in the world of SCM (Supply Chain Management). Data is considered to be driver of better decision-making process. Organizations using BDP are on average 5% more productive and 6% more profitable. The research portrays the current development in the fields of data science, predictive analysis and big data in supply chain industry. It is used to calculate statistics, predict demand, optimize events, calculate probabilities. Data mining is a major aspect of the current applications. Customer behavior is understood through the collected data to optimize and analyze marketing, supply and customize the products. It is also discussed about DPB as a profession and a rising demand for DPB professionals in the market.

Jianqian et al. [29] (2014), said estimation and forecasting demand in a dynamic market is required to scale ethe business and also sustain it. Therefore, statistical demand prediction models are on the rise. The paper deals with the demand prediction model for laptops sold by HP. The developed model uses regression trees and a varying-coefficient mode. The proposed method starts with a tree model that partitions the space of varying-coefficient variables, then uses boosting to improve the predictive performance as well as the regression coefficient. The performance of the proposed approach was examined in a simulation with an application to the marketing data. The dependence of the demand on the product prices are carefully plotted for different brands to find a correlation that can lead to better pricing of the products. This brings about a positive change in the form of increased demand. Various boosting algorithms are also tested to find out one with the maximum efficiency which is found out to be BRAND.

Wenzel et al. [30] (2019), published in this paper the current trend in the development of Machine Learning (ML) is the integration with Supply Chain Management (SCM) to form smart systems which can automate and improve efficiency of the SCM task model. The paper looks into the current developments and applications of ML in SCM and visualizes probable research gaps. It was demonstrated that in the SCM task model a single area could have different ML methods applied for a common goal. A large portion of the research is focused primarily on demand prediction. An investigation of ML methods for inter-company areas such as SRM and CRM could be promising for SCM. Majority of the research work is still conceptual and requires integration with the SCM model to be useful and widespread. The deployment phase lacks enough emphasis.

Zdravkovic [31] (2014), demonstrated artificial is the ability to perform complex intellectual tasks like humans by a machine. Machine learning is the ability portrayed by a machine to learn how to perform a task. The commonly used AI and ML systems in supply chain are demand forecasting and inventory planning, material sourcing, manufacturing decisions, quality assurance and delivery and logistics. Other than demand of products, the likeable features can also be explored through machine learning. Amazon uses autonomous fork lifts in its warehouse operations. Some organizations like amazon and uber eats are trying put self-driving/smart robots to provide delivery of goods. It is also used to analyze HR and finance data to find out about anomalies in the data, to verify documents and check employee details.

Rahul [32] (2016), said Artificial Intelligence is always used to solve complex problems which are beyond human computational skills. The sub-disciplines of AI such as GA's and expert systems are employed to address complex issue of Supply Chain Management. It involves inventory management, location planning, purchasing, freight consolidation and routing or scheduling problems. Expert systems a sub-discipline of AI, is used to help purchasing managers to evaluate the performance of prospective suppliers, optimize the information exchange amongst purchase personnel and reduces the time taken to make the make-or-buy decision. AI is completely armed with predictive analytics that can analyze clusters of data collected through various sources. Analyzing these data helps companies to develop an efficient form of supply chain management.

Raghav [33] (2019), demonstrated how Supply Chain Management is critical in almost every industry today and there is an increased interest to revolutionize it using AI applications, from its benefits to fully leveraging the vast amounts of data collected by industrial logistics, warehousing and transport systems. LLamasoft is an organization providing solutions to predictive analytics for demand forecasting. Its Demand Guru predictive modeling software uses Machine Learning to identify hidden patterns such as seasonal demand or correlations between external weather, demand and other influences in historical demand data to help businesses identify ways to cut costs and increase operational efficiency across their supply chains. Chyme by Univired is a chatbot which is a conversational interface used to communicate between human operators and sales/marketing automation services such as SAP's salesforce.

Elton et al. [34] (2018), stated that in the recent years AI has risen to be the major trend in automating systems to streamline efficiency and profit. Procurement and supply chains, along with the wealth of data they generate, are both ripe to
leverage the efficiencies and insights afforded by AI, and in some cases already are. Different areas of Supply Chain have been driven with AI. These include: Requisition/ PO processing, PO Acknowledgement and Delivery Assurance, Catalogue Management, Guided Buying, Invoice Processing and Payment, Help Desk and Support. As technology progresses more and more businesses and systems will adopt AI as it has a promising future.

Mansoor [35] (2020), evaluated how AI is revamping the operational process and facilitating cost-effective supply chain solutions. It provides analysis of leading companies and solutions that are leveraging AI in their supply chains and those they manage on behalf of others, with evaluation of key strengths and weaknesses of these solutions. The report also provides a view into the future of AI in Supply Chain Management (SCM) including analysis of performance improvements such as optimization of revenues, supply chain satisfaction, and cost reduction. The report provides detailed analysis and forecasts for AI in SCM by solution (Platforms, Software, and AI as a Service), solution components (Hardware, Software, Services), management function (Automation, Planning and Logistics, Inventory Management, Fleet Management, Freight Brokerage, Risk Management, and Dispute Resolution), AI technologies (Cognitive Computing, Computer Vision, Context-aware Computing, Natural Language Processing, and

Machine Learning), and industry verticals (Aerospace, Automotive, Consumer Goods, Healthcare, Manufacturing, and others).

Donald et al. [36] (2003), said that inventory management is becoming increasingly important in today's growing economy. New products are continuously being developed and placed in the market for consumer purchase. This invention relates to inventory management systems and, more particularly, to methods and systems for performing an inventory management process that uses an intelligent station to track and/or inventory items that are tagged with Radio Frequency Identification (RFID) tags. The inventory management process may include at least one of an out of stock control process, a shrinkage recognition process, a rapid product recall process, an alert monitor process, and a sales optimization process. Each of these processes may perform various tasks that are used to manage the inventory of items in the environment, such as monitoring inventory levels of the items, detecting misplaced items in the environment, and providing feedback information associated with the items based on detected events (e.g., suggested alternative locations for certain items based on sales data).

Joseph et al. [37] (1999), demonstrated how an inventory management system automatically monitors inventory amounts, provides information concerning inventory, and decides if an order for replacement inventory should be placed. This invention is related to inventory management systems and methods. In particular, the invention is related to vendor-managed inventory systems and methods. The system and method provide information concerning inventory amounts and inventory ordering to a manufacturing site and an inventory vendor. The system comprises at least one storage receptacle that stores inventory; at least one amount indicator that determines an inventory amount in each receptacle, each amount indicator generating inventory amount signals representative of inventory amounts in the receptacle; at least one inventory price source that provides inventory price information; and a control unit that receives the inventory amount signals from the amount indicator and inventory price information from the inventory price source. The control unit analyzes the inventory amount signals to determine amounts in the receptacle. The control unit also analyzes the amounts and inventory price information, and uses this information to determine if an inventory order should be placed.

Yiwei et al. [38] (2011), developed a system, method and computer program product are made for demand modelling and prediction in retail categories. The method uses time-series data comprising of unit prices and unit sales for a designated choice set of related products, with the time-series data obtained over a given sequence of sales reporting periods, and over a collection of stores in a market geography. Other relevant data sets from participating retail entities that include additional product attribute data such as market and consumer factors that affect retail demand are further used. A demand model for improved accuracy is achieved by individual sub-modelling method steps of: estimating a model for price movements and price dynamics from the time series data of unit-prices in the aggregated sales data; estimating a model for market share of each product in the retail category using the aggregated sales data and integrated additional product attribute data; and, estimating generating a model for an overall market demand in the retail category from the aggregated sales data.

Akio et al. [39] (2006), proposed a system to support a purchase or a production of a product by accurately predicting a sold amount of the product. A system that supports a purchase or a production of a product, the system including an input section for accepting an input of a history of a supplied amount and a sold amount of the products, a function generating section for representing a conditional probability function showing probability distribution of a sold amount when the sold amount is restricted by the supplied amount by means of a potential demand probability function including a parameter showing probability distribution of the sold amount when it is supposed that the sold amount is not restricted by the supplied amount and computing a value of the parameter maximizing a value of a likelihood function of the conditional probability function using the input history as a sample to generate the potential demand probability function, and a supplied amount computing section for computing a supplied amount of the product maximizing a profit by a sale of the product, based on the generated potential demand probability function and a predetermined selling price and supplying price of the product, and outputting the amount as a quantity of the product to be purchased or produced.

Stephen et al. [40] (2000), said manufacturing firms are subject to pressure to do everything faster, cheaper, and better. Firms are expected to continue to improve customer service by increasing on-time deliveries and reducing delivery lead-times. At the same time, they must provide this service more cheaply and utilize fewer assets. Increasingly, firms need to do this for a global marketplace. The author develops a model for positioning safety stock in a supply chain. They model the supply chain as a network, where the nodes of the network are the stages of a supply chain. We assume that each stage uses a base-stock policy to control its inventory. They also assume that each stage quotes a service time to its customers, both internal and external, and that each stage provides 100% service for these quoted service times. Finally, they assume that external customer demand is bounded. They show how to evaluate the inventory requirements at each stage as a function of the service times. For supply chains that can be modelled as spanning trees, they develop an optimization algorithm for finding the service times that minimize the holding cost for the safety stock in the supply chain.

3.2. BACKGROUND

Most small-scale business shut down due to getting a very low or no return on investment. This happens due to unwanted expenditure and ill-maintained inventory. To overcome the money barrier for such businesses, a smart inventory management system is required which can ease the predicting part of investment in raw materials and give a clear visual of the growth of the business.

3.3. MOTIVATION

In the current scenario of economic recession, all new establishments require a way to streamline profit and to avoid low return on investment and have a successful business.

As a programmer point of view, the project helps understand a wide array of topics like K-nearest neighbour, predictive analysis and python libraries such as Keras, NumPy etc.

IV. METHODOLOGY

The problem is divided into two parts: 1. **Forecasting demand** 2. **Calculating inventory variables.**

4.1. FORECASTING DEMAND:

Demand forecasting/prediction is the process of using historical data of orders to calculate future demand. To businesses, demand forecasting provides an estimate the amount of goods and services its customers will purchase in the foreseeable future.

The process is predicting demand can be divided into x steps:

- **Step 1: Collection of Historical Data**
  The first step for prediction is finding suitable data source for the problem. In our case, an inventory of medicines was taken into account. This dataset is sourced from Kaggle, an online dataset repository. It contains 8 medicines named - '#M01AB', '#M01AE', '#N02BA', '#N02BE', '#N05B', '#N05C', '#R03', '#R06'. Weekly order data is maintained in a CSV file. The format of the table is:

date	#M01AB	#M01AE	#N02BA	#N02BE	#N05B	#N05C	#R03	#R06

Column 1 – 'date' contains the date of the beginning of the week int the format 'MM-DD-YYYY'. The subsequent columns named after the medicines contain the weekly sale of the medicines. A sample screenshot of the dataset:

datum	# M01AB	# M01AE	# N02BA	# N02BE	# N05B	# N05C	# R03	# R06
1/5/2014	14	11.67	21.3	185.95	41	0	32	7
1/12/2014	29.33	12.68	37.9	190.7	88	5	21	7.2
1/19/2014	30.67	26.34	45.9	218.4	80	8	29	12
1/26/2014	34	32.37	31.5	179.6	80	8	23	10
2/2/2014	31.02	23.35	20.7	159.88	84	12	29	12

The dataset contains weekly orders from 01-05-2014 to 10-13-2019. Therefore, there are 248 entries in our dataset.

- **Step 2: Parsing the data**

Since we are using Python as the Backend Language, parsing a CSV file to computer understandable format is done via a library called **Pandas.** The CSV file called “salesweekly.csv” is opened.

- **Step 3: Processing the data**
  CSV format is called a comma-delimited format. The CSV file when opened with a text formatting software looks like this:

```
Medicine,Given Lead Time,Actual Lead Time
#M01AB,7,7
#M01AB,7,6
```

For easy computation purpose, this comma-delimited data needs to be converted to a data structure to operate on it. The library **NumPy** comes into play here. This converts the data to an array which aids in the process of using the data to calculate results.

```
C:\Users\abhim\Desktop\AI_inventory_management>python inventory.py
[[14.   29.33 30.67 ... 39.01 36.68 25.02]
 [29.33 30.67 34.   ... 36.68 25.02 32.35]
 [30.67 34.   31.02 ... 25.02 32.35 39.36]
 ...
 [47.33 36.52 44.01 ... 40.71 35.51 46.84]
 [36.52 44.01 40.99 ... 35.51 46.84 34.01]
 [44.01 40.99 45.18 ... 46.84 34.01 38.7 ]]
```

```
C:\Users\abhim\Desktop\AI_inventory_management>python inventory.py
[32.35  39.36  25.69  19.68  36.03  27.36  26.36  22.02  24.67  22.38
 25.02  17.71  23.34  29.03  31.68  21.02  27.35  26.01  33.67  28.01
 20.02  28.36  26.02  36.36  22.05  29.7   18.7   18.02  25.36  32.35
 23.7   23.115 19.69  25.67  40.67  31.67  28.35  31.06  28.69  25.02
 25.01  36.18  36.68  19.34  39.35  29.69  32.19  20.34  35.01  21.67
 43.35  41.68  27.02  42.    25.01  35.01  40.18  41.65  36.66  29.34
 22.    35.    35.68  50.33  35.34  28.34  41.67  39.84  36.36  30.51
 38.71  36.35  50.36  33.83  41.01  41.17  51.68  39.35  38.33  38.67
 41.22  44.65  45.33  42.66  48.17  29.98  32.49  36.97  32.01  31.65
 31.32  41.51  32.99  31.98  33.33  41.65  51.67  27.98  46.01  51.66 ]
```

- **Step 4: Choosing Prediction Algorithm**
  There are a number of Machine Learning based prediction models available to us. Some of these are K-Nearest Neighbours, Support Vector Machine (SVM), Linear Regression, Random Forest, etc. Each of these have their own advantages and disadvantages. There is no one-fits-all algorithm for Prediction analysis, so we tested out a few until a

suitable algorithm was found with decent accuracy. The python library used for the various machine learning prediction algorithms is **SKLearn.** For visualizing the results using graphs and plots we will use the **matplotlib** library.

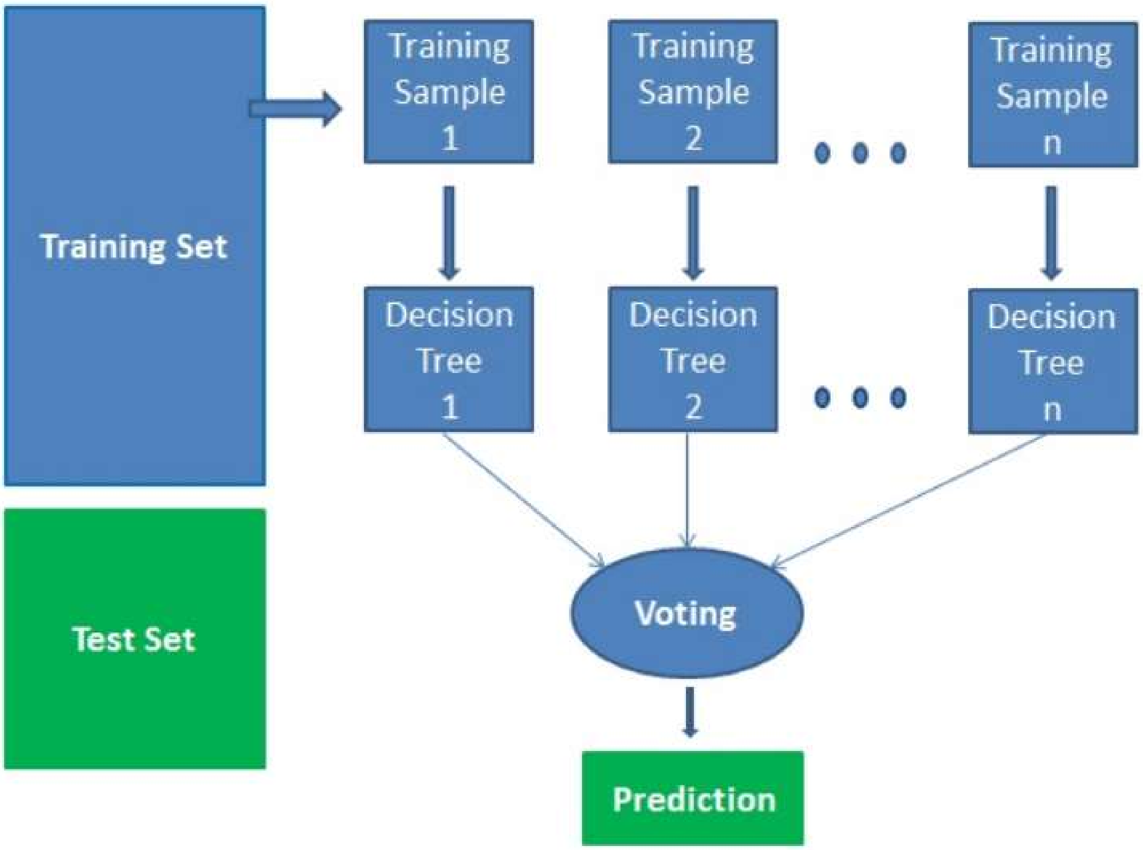
Random Forest:
Random forest is a supervised learning algorithm. It can be used for both classification and regression. In our case we will use the random forest regressor. It creates decision trees on randomly selected data samples, gets prediction from each tree and selects the best solution by the means of voting. It works on four steps:

Step 1: Select random samples from a given dataset.
In our case the dataset is weekly orders of the past 10 weeks.

Step 2: Construct a decision tree for each sample and get a prediction result from each decision tree.

Step 3: Perform a vote for each predicted result.

Step 4: Select the prediction result with the most votes as the final prediction.



Decision trees are a popular method for various machine learning tasks. because it is invariant under scaling and various other transformations of feature values, is robust to inclusion of irrelevant features, and produces inspectable models. However, they are seldom accurate. In particular, trees that are grown very deep tend to learn highly irregular patterns:
they overfit their training sets, i.e. have low bias, but high variance. Random forests are a way of averaging multiple deep decision trees, trained on different parts of the same training set, with the goal of reducing the variance. This comes at the expense of a small increase in the bias and some loss of interpretability, but generally greatly boosts the performance in the final model.

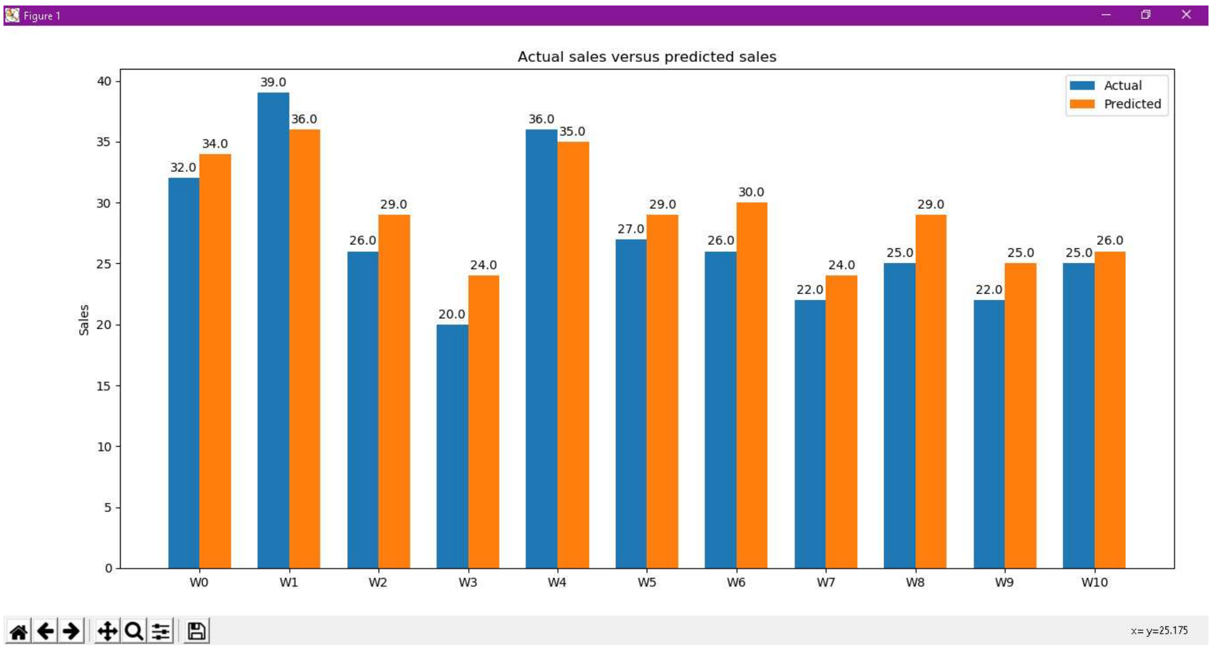
Forests are like the pulling together of decision tree algorithm efforts. Taking the teamwork of many trees thus improving the performance of a single random tree.

Random forests differ in only one way from this general scheme: they use a modified tree learning algorithm that selects, at each candidate split in the learning process, a random subset of the features. This process is sometimes called "feature bagging". The reason for doing this is the correlation of the trees in an ordinary bootstrap sample: if one or a few features are very strong predictors for the response variable (target output), these features will be selected in many of the *B* trees, causing them to become correlated.

Typically, for a classification problem with *p* features, $\sqrt{p}$ (rounded down) features are used in each split. For regression problems the inventors recommend *p/3* (rounded down) with a minimum node size of 5 as the default. In practice the best values for these parameters will depend on the problem, and they should be treated as tuning parameters.

Adding one further step of randomization yields extremely randomized trees, or ExtraTrees. While similar to ordinary random forests in that they are an ensemble of individual trees, there are two main differences: first, each tree is trained using the whole learning sample (rather than a bootstrap sample), and second, the top-down splitting in the tree learner is randomized. Instead of computing the locally optimal cut-point for each feature under consideration (based on, e.g., information gain or the Gini impurity), a random cut-point is selected. This value is selected from a uniform distribution within the feature's empirical range (in the tree's training set). Then, of all the randomly generated splits, the split that yields the highest score is chosen to split the node. Similar to ordinary random forests, the number of randomly selected features to be considered at each node can be specified. Default values for this parameter are $\sqrt{p}$ for classification and p for regression, where p is the number of features in the model.
The fine-tuning required in Random Forest regressor is the depth of the decision trees. It takes “max_depth” as a parameter to fix the depth of the tree. The deeper the tree, the more splits it has and it captures more information about the data. We fit each decision tree with different values of max_depth to find a suitable depth. The best accuracy of 82% was found with max_depth=10.

The algorithm has 2 variables: the independent variable and the dependent variable. The independent variable in our case is time, and the dependent variable is demand. We use 10 weeks of data to train the data. The 11th week's data is used to test the model and the accuracy. Following is the plot for 10 random weeks demand forecasted vs the actual sales:



The accuracy calculated was 82% which gave us an error limit of ±5 units of medicine. This was in our acceptable range and thus this algorithm is selected as our final algorithm.

- **Step 5: Predicting future demand**
  With the selection of a fitting algorithm and testing we can now move on with the prediction. The following data is predicted for the subsequent weeks:

```
C:\Users\abhim\Desktop\AI_inventory_management>python inventory.py
[34.00881486 35.83640627 29.4546001  24.01534105 34.75151045 29.00657496
 30.0599914  24.36764229 28.89136523 24.91321725 26.10184829 23.22691424
 25.00578764 27.02033211 30.15500952 22.43013257 26.15746571 27.02626882
 31.89574488 28.81225189 22.97371849 28.10296608 27.51255423 32.60143568
 24.49914295 30.50002924 22.81872967 22.43387465 26.29009638 32.02255183
 26.02964388 24.69086715 21.64322563 27.16142139 34.71108947 30.04237232
 29.3388616  29.3059182  27.924086   27.4607474  27.37643261 35.2199463
 34.75576282 25.10921121 35.33843211 29.7959232  35.48632805 23.7496016
 33.64064613 25.00801963 39.5684789  37.98219563 30.2232174  38.4693904
 26.16916714 36.19961613 35.89850932 39.66584334 35.36573923 31.37292605
 29.62146933 34.32593947 34.69913058 43.86029761 34.74374055 33.17965922
 40.41477968 36.43394827 36.63869039 33.40145889 38.63068054 35.22908379
 46.86460711 35.47821626 38.406743   38.8884083  45.57354942 37.19039402
 38.80374652 38.82200538 40.50504262 42.0911067  41.74154928 39.75552925
 43.02547825 36.87444097 36.62218396 36.45855361 33.98135927 33.66681916
 33.30759072 37.67845387 34.17739374 35.39120062 35.07235224 38.18361172
 41.28427962 32.58153041 41.14515539 44.80442932]
```

4.2. CALCULATING INVENTORY VARIABLES:

A smart inventory management system not only predicts the demand but also fine tunes the stock and reordering process to streamline profit in the business.

The different variables in Supply Chain Management are:

- Safety Stock: It is the extra stock that is maintained to mitigate the risk of stockouts, i.e. shortage in raw material, caused by uncertainties in supply and demand. Adequate safety stock levels permit business operations to proceed according to plan.
- Reorder Quantity: At the time of reordering an amount needs to be decided to strike a balance between two factors: having enough stock to sustain the business and mitigate risks and not having surplus stock that leads to unusable principal and also increases cost of inventory.
- Lead Time: The time taken between ordering of raw material and it reaching the inventory.

These two factors when calculated correctly can decrease the risk of failure of business by eternal factors and also maintaining enough inventory that the cost of sustenance is low and in case of failure, the loss isn't huge.

- **Step 1: Calculating statistics functions on Lead Time and Sales**
  The lead time is contained in a CSV file called ‘lead_time.csv’. This is parsed using **Pandas** library. The design of the file is as follows:

Medicine	Given Lead Time	Actual Lead Time

  A sample entry in the dataset is as follows:

Medicine	Given Leac	Actual Lead Time
#M01AB	1	0.857143
#M01AB	1	0.857143
#M01AB	1	1.285714

  The Given and Actual Lead time are in weeks calculated as number of days/7. Mean and standard deviation on Actual Lead time is calculated by Pandas function ‘.mean()’ and ‘.std()’. Using the 10 weeks dataset part 1 of the problem, average sales and standard deviation of sales is calculated.

- **Step 2: Calculating z-score in Normal Distribution**
  We’ve determined our desired service level to be 90%.
  The z value for a number of samples is given by the equation:

$$z_i = \frac{x_i - \bar{x}}{S}$$

  Where,
  x_i = value of ith sample
  $\bar{x}$ = mean of sample
  S = standard deviation of sample
  Averaging out this equation for the data present in our dataset, we obtain a z value of 1.2816.
  This z value can also be confirmed from the following table for a 90% level of confidence. Therefore, we take the z value as 1.28.

Service Level	Service Factor	Service Level	Service Factor
50.00%	00.00	90.00%	01.28
55.00%	00.13	91.00%	01.34
60.00%	00.25	92.00%	01.41
65.00%	00.39	93.00%	01.48
70.00%	00.52	94.00%	01.55
75.00%	00.67	95.00%	01.64
80.00%	00.84	96.00%	01.75
81.00%	00.88	97.00%	01.88
82.00%	00.92	98.00%	02.05
83.00%	00.95	99.00%	02.33
84.00%	00.99	99.50%	02.58
85.00%	01.04	99.60%	02.65
86.00%	01.08	99.70%	02.75
87.00%	01.13	99.80%	02.88
88.00%	01.17	99.90%	03.09
89.00%	01.23	99.99%	03.72

- **Step 3: Calculating Safety Stock**
  Safety stock will be calculated with the following formula:
  $$Safety\ Stock = \left(Z * std(sales) * \sqrt{mean(LT)}\right) + (Z * mean(sales) * std(LT))$$
  Where,
  Z = Z-Score based on Service Level (1.28)
  std(x) = Standard Deviation of x
  mean(x) = Mean of x
  sales = sale of the previous 10 weeks
  LT = Lead Time

  This is using a normal distribution with uncertainty on demand and dependent lead time. For situations where demand and lead time are linked, we consider using this formula. It could be that lead time causes uncertainty on demand or that demand is having an impact on lead times. Because variability can impact sales and vice versa, typically more safety stock is needed to account for these unpredictable variations.

  Quantity of Reorder will be calculated using the following formula:

$$QOR = Demand + \left(\left(1 - {accuracy}/{100}\right) * Demand\right) + Safety\ Stock$$

Where,

QOR = Quantity of Reorder
Demand = Predicted demand of the next week using Random Forest Algorithm
Accuracy = Accuracy of model calculated during Testing
Safety Stock = Safety Stock calculated in last step

With Demand, Safety Stock and Quantity of Reorder calculated we have achieved our objectives.

V. PLATFORM

5.1. BACKEND

CSV files called ‘sales_weekly.csv’, for sales data to train the model and test it is used, and ‘lead_time.csv’, for lead time data for safety stock calculation is used.

Python libraries are used to process and calculate the results:

- Pandas: To read and parse the CSV file
- NumPy: To convert CSV data to Array form for easy processing
- Math: To calculate the statistical variables
- Matplotlib: To visualize the data using graphs and plots
- SKLearn: To implement Machine Learning Prediction Algorithms like Random Forest, Linear Regression etc.

5.2. FRONTEND

The platform used to execute the system is **CMD** and the language used for writing the script for the system is **Python3.**

VI. SAMPLE CODING

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import pickle
from sklearn import svm
from sklearn.ensemble import RandomForestRegressor

#Array Creation for med1
x1 = list()
y1 = list()
for i in range(len(med1)-10):
    x = np.array(med1.loc[i:i+9])
    y = np.array(med1.loc[i+10])
    x1.append(x)
    y1.append(y)
x1 = np.array(x1).reshape(292,10)
y1 = np.array(y1).reshape(292,)

#Random Forests 85%
reg = RandomForestRegressor(max_depth=10,random_state=10)
reg.fit(x1,y1)
print(reg.score(x1,y1))
p = reg.predict(x1)

#Save model1
filename = 'model1.sav'
pickle.dump(reg, open(filename, 'wb'))
model1 = pickle.load(open(filename, 'rb'))

#Read data from table
data = pd.read_csv("salesweekly.csv")
data.drop(0)
data.drop("datum",axis=1,inplace=True)
med1 = data[["M01AB"]]
med2 = data[["M01AE"]]
med3 = data[["N02BA"]]
med4 = data[["N02BE"]]
med5 = data[["N05B"]]
med6 = data[["N05C"]]
med7 = data[["R03"]]
med8 = data[["R06"]]

#-------------------------------------------------------------------------
```

```
#Take inputs
product = ['#M01AB', '#M01AE', '#N02BA', '#N02BE', '#N05B', '#N05C', '#R03
', '#R06']
df = pd.read_csv(r'lead_time.csv', index_col=0)
index = int(input("Enter index="))
print("Enter sales")
currentsales = float(input())
print("Finding data for "+product[index]+"....")

#-------------------------------------------------------------------------

#Choose model based on index
if index == 0:
    x = np.array(med1.loc[len(med1)-9:])
    x = np.append(x,currentsales).reshape(1,10)
    filename = 'model1.sav'
    accuracy = 0.82

if index == 1:
    x = np.array(med2.loc[len(med2)-9:])
    x = np.append(x,currentsales).reshape(1,10)
    filename = 'model2.sav'
    accuracy = 0.77

if index == 2:
    x = np.array(med3.loc[len(med3)-9:])
    x = np.append(x,currentsales).reshape(1,10)
    filename = 'model3.sav'
    accuracy = 0.86

if index == 3:
    x = np.array(med4.loc[len(med4)-9:])
    x = np.append(x,currentsales).reshape(1,10)
    filename = 'model4.sav'
    accuracy = 0.94

if index == 4:
    x = np.array(med5.loc[len(med5)-9:])
    x = np.append(x,currentsales).reshape(1,10)
    filename = 'model5.sav'
    accuracy = 0.86

if index == 5:
    x = np.array(med6.loc[len(med6)-9:])
    x = np.append(x,currentsales).reshape(1,10)
```

```
        filename = 'model6.sav'
        accuracy = 0.77

    if index == 6:
        x = np.array(med7.loc[len(med7)-9:])
        x = np.append(x,currentsales).reshape(1,10)
        filename = 'model7.sav'
        accuracy = 0.87

    if index == 7:
        x = np.array(med8.loc[len(med8)-9:])
        x = np.append(x,currentsales).reshape(1,10)
        filename = 'model8.sav'
        accuracy = 0.93

    #---------------------------------------------------------------------------

    #Calculate Demand
    model = pickle.load(open(filename, 'rb'))
    demand = model.predict(x)
    print("The predicted demand is: ")
    print(demand[0])
    mean1 = np.mean(x)
    std1 = np.std(x)

    #Inventory
    def lt_mean(index):
        #print(df['Actual Lead Time'][str(product[index])])
        return df['Actual Lead Time'][str(product[index])].mean()

    def lt_std(index):
        return df['Actual Lead Time'][str(product[index])].std()

    def ss_cal(z,prod_mean,prod_std,mean1,std1):
        ss = (z*std1*np.sqrt(prod_mean))+(z*mean1*prod_std)
        return ss

    def qor_cal(demand, accuracy, ss):
        qor = demand+((1-accuracy)*demand)+ss
        return qor

    prod_mean=lt_mean(index)
    prod_std=lt_std(index)

    z=1.28
```

```
safety_stock= np.ceil(ss_cal(z,prod_mean,prod_std,mean1,std1))
print("Required Safety Stock=")
print(safety_stock)

qor = np.ceil(qor_cal(demand, accuracy, safety_stock))
print("Required Quantity of Reorder=")
print(qor[0])
```

VII. RESULT

7.1. TEST CASE 1

Input:

Index = 0
Sales = 30

Output:

Predicted demand = 34.7932
Required Safety Stock = 24.0
Required Quantity of Reorder = 66.0

7.2. TEST CASE 2

Input:

Index = 1
Sales = 20

Output:

Predicted demand = 24.7989
Required Safety Stock = 16.0
Required Quantity of Reorder = 47.0

VIII. DISCUSSION

Safety stock refers to the minimum amount of inventory the person should have available at all times. This is to compensate for any sudden demands and to ensure that the needs of all clients are met.

The quantity of reorder refers to the amount of inventory the person needs to reorder. It is based on the demand predicted and its accuracy.

If the inventory falls below the safety stock, inventory should automatically be reordered.

$$Safety\ Stock = \left(Z * std(sales) * \sqrt{mean(LT)}\right)$$

$$+(Z * mean(sales) * std(LT))$$

For the first test case, we have:
Z = 1.28
std(sales) = 10.63
mean (LT) = 1.057
mean(sales) = 35.085
std (LT) = 0.204

From this we can see that safety stock is:
SS = (1.28 * $\sqrt{1.057}$) + (1.28 * 35.085 * 0.204)
Therefore, the safety stock will be 24.

$$QOR = Demand + \left(\left(1 - {}^{accuracy}/_{100}\right) * Demand\right) + Safety\ Stock$$

Demand = 34.793
Accuracy = 82%
Safety Stock = 24
QOR = 34.793 + ((1-0.82) *34.793) + 24
Therefore, the Quantity of Reorder will be 66.

IX. CONCLUSION & FUTURE SCOPE

In this project, we succeeded in predicting the demand of 8 different products based on 10 weeks' worth of sales. With the help of this demand, we were also able to calculate the safety stock as well as the quantity that needs to be reordered. In the future, we can make significant improvements in this system by adding an interface to make it easier to work with. We can also make improvements with regards to the accuracy of the machine learning models as and when more data is obtained.

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