

Inventory Management Optimization with Data Analytics for a Trading Company

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المخلص

Abstract

Distributors, manufacturers, and suppliers face the daunting challenge of inventory control. Each supply management problem that arises has ramifications. To satisfy supply and demand, inventory optimization will ensure that the correct commodity is available in the right amounts, at the right price, and in the right places. Furthermore, companies that optimize their inventory can reduce stock levels and, as a result, prevent bearing expenses and obsolescence write-downs. Data analytics helps suppliers and marketers assess their stocking goals and whether any upstream or downstream problems need to be resolved, which is critical in resource control and optimization processes. This study aims to explore how inventory management optimization, supported by data analytics, would be beneficial for a trading company operating in Oman. Currently, trading companies can only solve inventory management problems by either hiring expensive offshore software or using open-source software with little to no knowledge on how to adapt that software to suit specific needs. An online inventory management system is developed using the Java language and MySQL as the database server. Optimization is performed using the Orange data mining tool. The methodology chosen for application development is the Dynamic Systems Development Method. An interview has been conducted with a trading company employee for data collection purposes and the testing was done to ensure optimal performance. Data analytics was performed on the data collected from the online system and data mining was applied by applying feature reduction methods to optimize the results. The study showed a promising result to provide insights on the latest business trends and access the inventory effectively and efficiently.

Keywords: Classification, Data Analytics, Inventory Management, Optimization, Random Forest.

يواجه الموزعون والمصنعون والموردون التحدي الصعب المتمثل في مراقبة المخزون. لذا فإن كل مشكلة في إدارة التوريد تنشأ لها تداعيات. لذا فإن تلبية العرض والطلب لتحسين المخزون توفر السلعة الصحيحة بالكميات المناسبة وبالسعر المناسب وفي الأماكن المناسبة. علاوة على ذلك، يمكن للشركات التي تعمل على تحسين مخزونها أن تقلل من مستويات المخزون، ونتيجة لذلك، تمنع نفقات تحمل التكاليف والتقاعد. تساعد تحليلات البيانات الموردين والمسوقين على تقييم أهداف التخزين الخاصة بهم وما إذا كانت هناك حاجة إلى حل أي مشاكل في المراحل الأولية أو النهائية، وهو أمر بالغ الأهمية في عمليات التحكم في الموارد والتحسين. تهدف هذه الدراسة إلى استكشاف كيف سيكون تحسين إدارة المخزون، بدعم من تحليلات البيانات، مفيداً لشركة تجارية تعمل في عمان. في الوقت الحالي، يمكن للشركات التجارية فقط حل مشاكل إدارة المخزون إما عن طريق الاستعانة ببرامج خارجية باهظة الثمن أو باستخدام برامج مفتوحة المصدر مع القليل من المعرفة أو عدم معرفتها بكيفية تكيف هذا البرنامج ليناسب الاحتياجات المحددة. تم تطوير نظام إدارة المخزون عبر الإنترنت باستخدام لغة Java و MySQL كخادم قاعدة بيانات. يتم إجراء التحسين باستخدام أداة استخراج البيانات

من Orange. المنهجية المختارة لتطوير التطبيق هي طريقة تطوير الأنظمة الديناميكية. تم إجراء مقابلة مع موظف شركة تجارية لأغراض جمع البيانات وتم إجراء الاختبار لضمان الأداء الأمثل. تم إجراء تحليلات البيانات على البيانات التي تم جمعها من النظام عبر الإنترنت وتم تطبيق التنقيب عن البيانات من خلال تطبيق طرق تقليل الميزات لتحسين النتائج. أظهرت الدراسة نتيجة واحدة لتقديم رؤى حول أحدث اتجاهات الأعمال والوصول إلى المخزون بفعالية وكفاءة.

الكلمات الرئيسية: التصنيف ، تحليلات البيانات ، إدارة المخزون ، التحسين ، الغابة العشوائية.

1. Introduction

The manufacturing industry is a vital component for the economy of a country. It is the key component in a country's Gross Domestic Product (GDP). Due to this importance, the manufacturing industry has to operate as efficiently as possible in order to reduce costs, wastage, and increase profitability in the process. The low production cost gives the company a price advantage over competitors both within the country and in the export market.

The manufacturing industry will design and manufacture products using raw materials that may be procured locally or imported from outside the country. These raw materials are stored either in a warehousing facility within the premises or in an off-premises central warehousing facility. The finished goods are also stored in a warehouse which may be on or off-premises. These warehouses act as a transit station to store inventory temporarily before it is either sent to production, in the case of raw materials, or to sales, in the case of finished goods. Therefore, the warehouse is a crucial area in the supply chain process that needs to be managed properly.

An efficient warehouse is one where the inventory is sorted and kept in a manner which makes it easily accessible, identifiable and moveable. In addition to this, there are times when the warehousing department needs to know the status of the goods, especially when they are in transit, in order to prepare the space and finish the receiving formalities well in advance instead of wasting time and beginning preparations late. Such information must be trickled down to all concerned and using phone calls and/or emails is very inefficient.

The warehousing department plays a very crucial role and acts as an intermediary between the procurement department, the production department, and the sales

department. Therefore, a key tool in ensuring these departments are aligned and the company runs efficiently is an Inventory Management System (IMS) or Warehouse Management System (WMS). It ensures real-time access to stock level reports, usage reports etc. while ensuring that proper picking methods (FIFO/LIFO) are followed.

The objective of the study is (1) To provide users with an easy-to-use system that fulfils all their inventory management needs, such as knowing the status of goods in transit, suppliers of goods, and item storage within the warehouse. (2) To establish vital communication between the company's employees and their suppliers and customers, keeping each other up-to-date on all available information about the stock. (3) To review existing literature and similar systems in order to obtain a better understanding of how to model the system to meet the client requirements. (4) To keep in touch with the company that uses this system in order to fulfil any future needs they have.

2. Background Study

Inventory management exists only to serve the customer with a company's inventory. The inventory can include finished goods or materials. If a company wishes to service a customer, they must put the customer's viewpoint first and consider factors such as availability in the correct quantity at the right time, place, and cost. The author further states that good inventory planning covers fluctuations in demand, forecast errors, and supply errors, since customer demand is always changing and can never be predicted to a high level of accuracy. The primary goal of a company is to minimize costs on inventory while still meeting the functional requirements. Here, improved forecasting and process reliability allows for reductions in inventory, but keeps the same level of manufacturing efficiency and customer service. The process of inventory management is continuous, meaning that standards have to be maintained constantly. A basic understanding of the processes within inventory management is the minimum requirement for all involved personnel [1].

Inventory management must be thought of by companies very carefully, as any mistakes can be costly. Good inventory management leads to higher profitability and reduced vulnerability in competitive markets and globalization. Therefore, strategy evaluation and optimal decision-making are the key in the optimization of the total flow of materials to and from the company, be it suppliers, manufacturers, or end users. The authors further state that managers have to make appropriate decisions at the operational, strategic, and tactical level. A company should maintain robust supply chains in order to remain competitive in the industry; they must be responsive to changes. The authors then discuss two approaches to solve inventory issues: analytic and simulation. Simulation approach involves managers testing out different scenarios before deciding on the one with the best results. The analytic approach is more simplistic in nature, and this is the method most decision makers prefer for this reason [2].

3. Literature Review

Large scale data can influence decisions regarding inventory management and how it can make a company competitive. They state that, in recent years, more and more data has become readable by machines. This paved the way for applications that could predict results, and the authors cite two examples, one of them being the prediction of video game demand based on search engine query results. Inventory management is mainly dependent on the demand for the company's stock. Using the prediction data, the company can decide how much to stock their shelves with their products.

Using this data, the authors created inventory prescriptions for each location and period when stock will be replenished. The performance of the method is then compared to the performance of the perfect-forecast policy, which has unparalleled knowledge on future demand, and the performance of a data-driven policy. When the authors created a graph out of the performance data, it was discovered that their method was 88% close to the performance of the perfect-forecast policy in terms of the volumes of sell-through [3].

The authors further state that big data analysis can be performed with the help of various software tools. They list the benefits of using big data analytics such as faster market response time, recognizing revenue streams, improved efficiency, increase profitability, and enhancing relationships with end users. The method also allows the organization to get a better understanding of their data, and so classify and analyze that data accordingly. The authors conclude that companies should strive to employ big data analytics for various reasons. They claim it improves the profitability of the organization based on demand using customer retention [4].

The authors list drawbacks that occur in manual inventory management; they include human errors, increased labor costs from operating a manual system, and poor efficiency in materials-handling. Computing technologies have demonstrated great improvements to warehouse management in recent years, introducing benefits such as tighter inventory control, lower response time, and a more diverse variety of stock-keeping units. [5] Also shows that RFID technology has become more popular in this sector. The authors present multiple papers that show the benefits of employing such technology. These include eliminating inaccurate data records, the maximum utilization of inventory within a company, shelf space and reduction in operational errors. One of the RFID systems examined used a decision maker, which improved the evaluation of company operations. The authors continue to look into multiple RFID systems in detail and their impact, which is generally positive, on inventory management. They then conclude by summarizing how RFID systems can automate the inventory management tasks and improve company operational efficiency. They recommend that companies use simulation tools to decide how best to employ such systems [5].

The impact of data analytics on various sectors of operations management. Due to the recent advances in machine learning technologies and optimization

methodologies, as well as the growing availability of data, there has been an increasing usage of data analytics to solve problems in operations management. The authors have reviewed such changes in different sectors, such as location operations and inventory management. Data analytics is defined by the authors as data that is used to create models that lead to decisions to create value. In inventory management, data analytics may use data such as weather forecasts and consumer price index. The authors look at other papers that have explored methods to improve inventory decision-making [6].

[7] Proposed two approaches to inventory decisions, which are data-driven. The first approach involves risk minimization and finding the order quantity by solving a single problem; decision variables is the decision rule that maps the features to the order quantity, and thus minimize the sample-based estimate of the cost. The second approach is to model the conditional demand distribution using kernel regression and apply a sorting algorithm to determine the optimal order quantity. The authors of that paper discovered that their proposed methods outperformed the benchmark for best practices by 24%. [6] Also look a number of other papers and the proposed methods within them, describing how to implement them and their success rates.

The technologies employed by these approaches differ significantly. The authors state that while they both aim to revolutionize and deployment and managing businesses through cloud computing, there is no knowledge that guides in choosing which technology is better. Therefore, a customer should examine both technologies and select which one best suits their needs. They must also be an expert in one of the technologies for successful deployment.

4. Methodology

For this project, the Dynamic System Development Method (DSDM) was chosen for the implementation of the project. The methodology has been attributed to a high number of successful projects compared to traditional methodologies for a number of reasons [8] [9]

[10][11][12]. Establishes that a change in requirements is always expected in a project life cycle, and as such there is an increasing demand for a project framework with the least amount of risk. By switching from a traditional methodology to the Dynamic System Development Method, the cost of development, time, and overall productivity are impacted positively. Dynamic System Development Method is well-suited for changing requirements, with a focus on continuous user involvement and frequent delivery. Therefore, the methodology can satisfy the aforementioned demand. The methodology strictly follows the project time and budget that was established at the beginning of the life cycle. The methodology also has a strong reliance on system testing and cooperation between the user and the developer, thus eliminating as many software errors as possible [8].

5. Design

Figure 1. Shows the relation between the user, system, and database. The user wishes to access the database, the

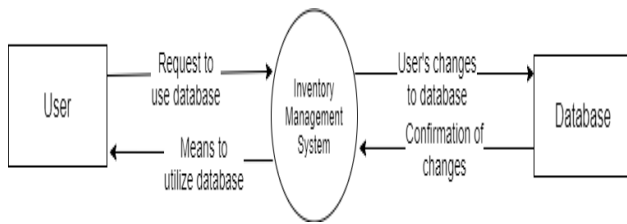


Figure 1. Level 0 Data Flow Diagram

system will provide the means to do so, and pass the requested changes onto the database. Figure 2. Shows the relation between the user, system, and database in more detail. Reports are also involved. The user can either request changes to the database or request a report to be made from the data stored in the database.

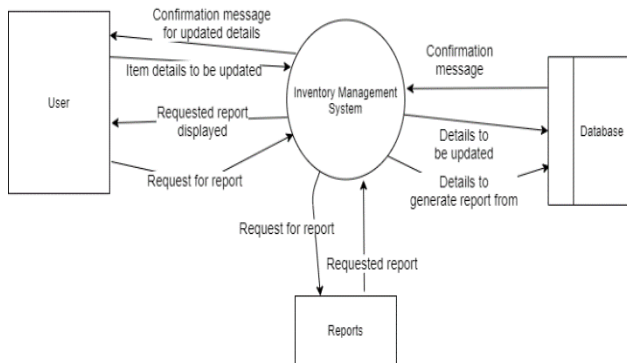


Figure 2. Level 1 Data Flow Diagram

Figure 3. Shows all the attributes and relationships between the entities in the system. Item includes all attributes of the items. Data analytics can be performed on the item data. Report's attributes include the type, the data displayed, and the date of creation.

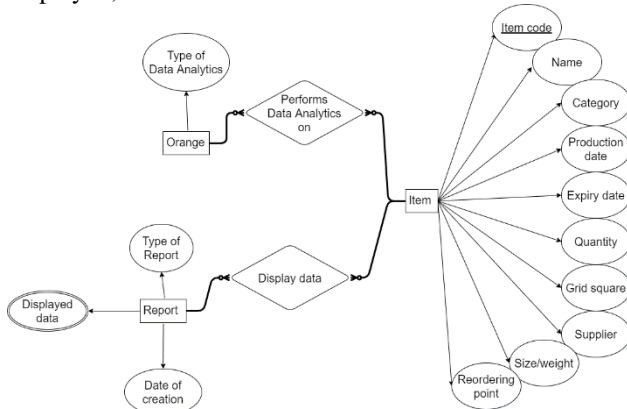


Figure 3. Entity Relationship Diagram

Figure 4. Shows the steps involved in the data curation process. First, the data is cleansed to eliminate any corrupt data, and is then sent to pre-processing where the data is modified after being exported from the system into an Excel spreadsheet. The data is then classified using classifications like Random Forest and Tree, before having its performance evaluated through a confusion

matrix. Feature reduction will be applied through Principal Component Analysis. Finally, the data will be interpreted to extract some useful meaning.

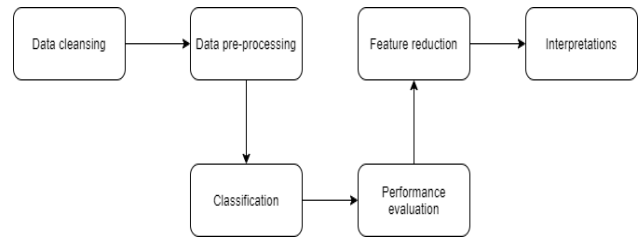


Figure 4. Data curation model

Figure 5. The data is imported, with the target set as the “reorder” field. Rule induction is applied using CN2 Rule Induction and can be viewed separately using the CN2 Rule Viewer. The data is classified using Random Forest, Tree, Naïve Bayes, SVM, Logistic Regression, and kNN. It can be discretized, ranked, tested and scored, and then put through a confusion matrix to evaluate the accuracy of results from those classifications. The performance can also be evaluated using ROC (receiving operating characteristic) analysis and Principal Component Analysis. The data is visualized through RadViz.

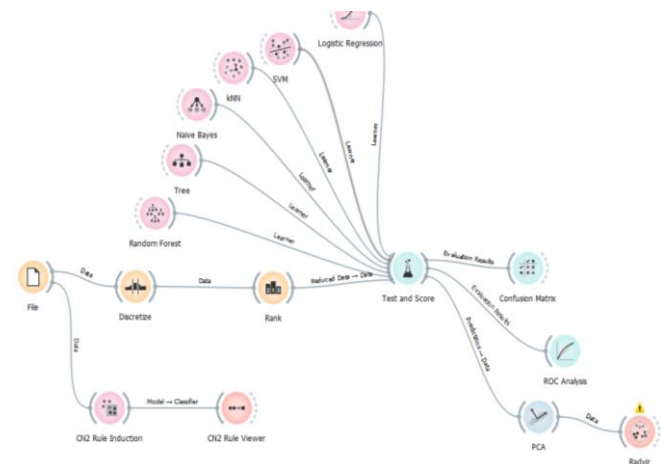


Figure 5. Data analytics model

6. Implementation

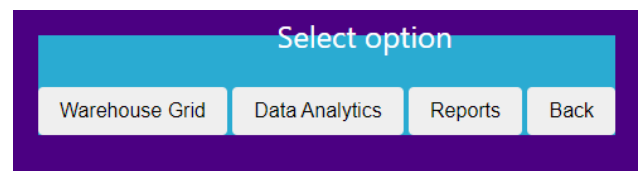


Figure 6. Main Menu.

The main menu page as shown in Figure 6. allows the user to select which page they would like to go to by clicking the appropriate button. They may also return to the login screen by clicking “Back.”

ID	Name	Category	Production date	Expiry date	Quantity	Supplier	Size	Unit of measurement	Recording point
1	Carrot	Vegetable	2021-01-01	2022-01-01	50	Haroon	5.0	kilograms	10
2	Water	Liquid	2021-01-01	2022-01-01	200	Haroon	200.0	liters	10
41	Dragon fruit	Fruit	2021-01-01	2022-01-01	100	John	75.0	kilograms	10
42	Papaya	Fruit	2021-01-01	2022-01-01	100	John	40.0	kilograms	10
43	Banana	Fruit	2021-01-01	2022-01-01	100	John	50.0	kilograms	10
44	Brinjal	Vegetable	2021-01-01	2022-01-01	100	John	25.0	kilograms	10
45	Kashan	Vegetable	2021-01-01	2022-01-01	100	John	25.0	kilograms	10
46	Turnip	Vegetable	2021-01-01	2022-01-01	100	John	25.0	kilograms	10
47	Cucumber	Plant	2021-01-01	2022-01-01	100	John	25.0	kilograms	10
48	Tomato	Vegetable	2021-01-01	2022-01-01	100	John	25.0	kilograms	10
49	Mango	Fruit	2021-01-01	2022-01-01	100	John	25.0	kilograms	10
50	Red jamun	Vegetable	2021-01-01	2022-01-01	100	John	25.0	kilograms	10
51	Plum	Fruit	2021-01-01	2022-01-01	100	John	2510.0	kilograms	10

Figure 7. Grid Square Page.

Each grid square page displays a certain number of items depending on where those items are stored in the warehouse. The pages also allow the user to add new items, update existing items, or delete items from the database by filling in the required fields. They can return to the main menu by clicking “Back.” As shown in Figure 7.

7. Results and Discussion

(Chen et al., 2018) discusses different algorithms that extract some meaning out of the dataset. The algorithms selected for this project were principal component analysis, regression analysis (logistic regression), association rules (CN2 rule induction), Bayesian classification (Naive Bayes), and decision tree. For prediction and early warning, support vector machines algorithm was selected.

Data visualization is done through RadViz [13][14][15][16][17][18][19].

Based on these results, the random forest algorithm had the highest accuracy of all six algorithms. Random forest yielded the highest accuracy with 97% with no transformation or feature selection, cross validation with twenty folds, and non-stratified method.

Table 1. No transformation or feature selection, cross validation with five folds, non-stratified

Model	Accuracy	Sensitivity	F-Measure	Specificity	Recall
Random Forest	0.96	0.85	0.85	0.85	0.85
Tree	0.94	0.91	0.91	0.92	0.91
Naive Bayes	0.91	0.74	0.74	0.74	0.74
SVM	0.81	0.67	0.67	0.72	0.67
kNN	0.79	0.62	0.62	0.62	0.62
Logistic Regression	0.45	0.35	0.29	0.25	0.35

Table 2. No transformation or feature selection, cross validation with ten folds, non-stratified

Model	Accuracy	Sensitivity	F-Measure	Specificity	Recall
Random Forest	0.97	0.87	0.87	0.87	0.87
Tree	0.94	0.91	0.91	0.92	0.91
Naive Bayes	0.92	0.75	0.75	0.76	0.75
SVM	0.82	0.68	0.68	0.73	0.68
kNN	0.81	0.66	0.66	0.67	0.66
Logistic Regression	0.42	0.39	0.33	0.28	0.39

Table 3. No transformation or feature selection, cross validation with twenty folds, non-stratified

Model	Accuracy	Sensitivity	F-Measure	Specificity	Recall
Random Forest	0.97	0.85	0.85	0.85	0.85
Tree	0.96	0.93	0.93	0.93	0.93
Naive Bayes	0.92	0.76	0.76	0.77	0.76
kNN	0.82	0.67	0.67	0.68	0.67
SVM	0.81	0.63	0.63	0.69	0.63
Logistic Regression	0.38	0.42	0.35	0.29	0.42

Table 4. Transformation with equal-frequency discretization, no feature selection, cross validation with five folds, non-stratified

Model	Accuracy	Sensitivity	F-Measure	Specificity	Recall
Random Forest	0.91	0.72	0.72	0.73	0.72
Tree	0.86	0.71	0.71	0.72	0.71
kNN	0.89	0.74	0.74	0.74	0.74
SVM	0.85	0.70	0.70	0.71	0.70
Logistic Regression	0.91	0.71	0.71	0.71	0.71
Naive Bayes	0.90	0.70	0.70	0.70	0.70

Table 5. Transformation with equal-frequency discretization, no feature selection, cross validation with ten folds, non-stratified

Model	Accuracy	Sensitivity	F-Measure	Specificity	Recall
Tree	0.88	0.68	0.68	0.69	0.68
SVM	0.85	0.64	0.64	0.64	0.64
Random Forest	0.90	0.66	0.66	0.66	0.66
Naive Bayes	0.90	0.70	0.70	0.70	0.70
Logistic Regression	0.91	0.71	0.71	0.71	0.71
kNN	0.90	0.74	0.74	0.75	0.74

Table 6. Transformation with equal-frequency discretization, no feature selection, cross validation with twenty folds, non-stratified

Model	Accuracy	Sensitivity	F-Measure	Specificity	Recall
Logistic Regression	0.91	0.68	0.68	0.68	0.68
Random Forest	0.91	0.67	0.67	0.68	0.67
kNN	0.90	0.73	0.73	0.74	0.73
Naive Bayes	0.90	0.72	0.71	0.73	0.72
Tree	0.88	0.66	0.66	0.67	0.66
SVM	0.86	0.62	0.62	0.62	0.62

Table 7. Transformation with equal-frequency discretization, feature selection with ranking (gini decrease), cross validation with five folds, non-stratified

Model	Accuracy	Sensitivity	F-Measure	Specificity	Recall
Random Forest	0.90	0.72	0.72	0.73	0.72
Tree	0.86	0.71	0.71	0.72	0.71
kNN	0.89	0.74	0.74	0.74	0.74
SVM	0.84	0.70	0.70	0.71	0.70
Logistic Regression	0.91	0.71	0.71	0.71	0.71
Naive Bayes	0.90	0.70	0.70	0.70	0.70

Table 8. Transformation with equal-frequency discretization, feature selection with ranking (gini decrease), cross validation with ten folds, non-stratified

Model	Accuracy	Sensitivity	F-Measure	Specificity	Recall
Random Forest	0.91	0.71	0.71	0.71	0.71
Tree	0.88	0.68	0.68	0.69	0.68
kNN	0.90	0.74	0.74	0.75	0.74
SVM	0.85	0.64	0.64	0.64	0.64
Logistic Regression	0.91	0.71	0.71	0.71	0.71
Naive Bayes	0.90	0.70	0.70	0.70	0.70

Table 9. Transformation with equal-frequency discretization, feature selection with ranking (gini decrease), cross validation with twenty folds, non-stratified

Model	Accuracy	Sensitivity	F-Measure	Specificity	Recall
Random Forest	0.89	0.65	0.65	0.65	0.65
Tree	0.88	0.66	0.66	0.67	0.66
kNN	0.90	0.73	0.73	0.74	0.73
SVM	0.83	0.62	0.62	0.62	0.62
Logistic Regression	0.91	0.68	0.68	0.68	0.68
Naive Bayes	0.90	0.72	0.71	0.73	0.72

Table 10. Transformation with equal-width discretization, feature selection with ranking (gini decrease), cross validation with twenty folds, non-stratified

Model	Accuracy	Sensitivity	F-Measure	Specificity	Recall
Random Forest	0.91	0.69	0.69	0.69	0.69
Tree	0.90	0.70	0.70	0.70	0.70
kNN	0.86	0.72	0.71	0.72	0.72
SVM	0.83	0.66	0.66	0.67	0.66
Logistic Regression	0.90	0.64	0.64	0.64	0.64
Naive Bayes	0.87	0.71	0.70	0.72	0.71

		Predicted			Σ
		High	Low	Medium	
Actual	High	22	0	8	30
	Low	2	23	4	29
	Medium	10	4	27	41
Σ		34	27	39	100

Figure 10. Confusion matrix for random forest algorithm.

*** CN2 Rule Viewer

	IF conditions	THEN class	Distribution	Probabilities [%]	Quality	Length
0	id ≥ 86.0	reorder=Medium	[0, 0, 15]	6 : 6 : 89	-0.00	1
1	id ≥ 69.0	reorder=Low	[0, 17, 0]	5 : 90 : 5	-0.00	1
2	id ≥ 51.0	reorder=High	[18, 0, 0]	90 : 5 : 5	-0.00	1
3	id ≥ 38.0	reorder=Medium	[0, 0, 13]	6 : 6 : 88	-0.00	1
4	id ≥ 26.0	reorder=High	[12, 0, 0]	87 : 7 : 7	-0.00	1
5	id ≥ 13.0	reorder=Medium	[0, 0, 13]	6 : 6 : 88	-0.00	1
6	id ≤ 2.0	reorder=Low	[0, 2, 0]	20 : 60 : 20	-0.00	1
7	id ≤ 4.0	reorder=Low	[0, 2, 0]	20 : 60 : 20	-0.00	1
8	id ≤ 6.0	reorder=Low	[0, 2, 0]	20 : 60 : 20	-0.00	1
9	id ≤ 8.0	reorder=Low	[0, 2, 0]	20 : 60 : 20	-0.00	1
10	id ≤ 10.0	reorder=Low	[0, 2, 0]	20 : 60 : 20	-0.00	1
11	id ≤ 12.0	reorder=Low	[0, 2, 0]	20 : 60 : 20	-0.00	1
12	TRUE	reorder=Medium	[30, 29, 41]	30 : 29 : 41	-1.566	0

Figure 11. CN2 Rule Inducer Algorithm.

Consists of a table that displays the probabilities under several conditions.

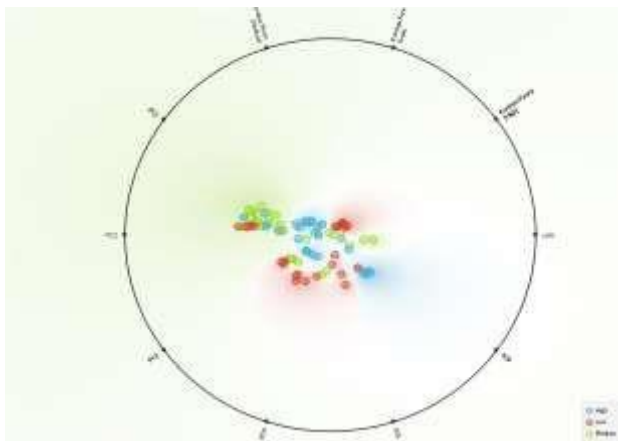


Figure 12. Visualization of Principal Component Analysis and Random Forest through RadViz.

Consists of a circle with multiple dots around different positions. Results show that medium values are more common towards PC1, Random Forest (Medium), and PC2, while low and medium values are geared towards the center.

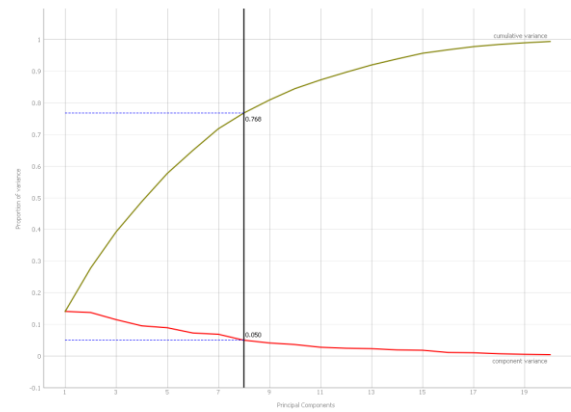


Figure 13. Principal Component Analysis.

8. Conclusion

The study met the requirement of the study conducted, save for establishing communication between the supplier and customer due to a lack of expertise. The system was developed with Omani trading companies in mind and built for their needs specifically. With this system, updating stock and tracking items within the warehouse are much easier tasks using up-to-date methods of inventory management optimization. The system will keep track of which item is stored in which grid square and stock counting is automatized. However, the system could not be deployed due to the high cost of setting up a Java web application for public use.

The limitation of the study is that the system uses an excel file to be fed into the data mining tool. This can be done in a real-time situation to provide information quickly.

For future works, the online system can be embedded with real-time data analytics to help the logistics sector of Oman.

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9. References

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