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# RECOMMENDATION-BASED SALES PERFORMANCE IMPROVEMENT FOR BUSINESS PERSPECTIVE VIA CLASSIFICATION MODEL

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**ABSTRACT:** In present day, E-commerce is one of the fast-developing business models among many. The key aspect of E-commerce nowadays is shopping from any place at any time. In real time as vast amount of data are generated because of vast population of people and devices that are connected, have created challenges to handle the huge data stream that are arriving from every device. The data stream click is captured by another famous approach that is called as Web Data Mining. Every time a customer seeks for some details, or to browse some of the category of products or to do any transaction. All these functions leave trials of data as a resource for web data mining, which is required to portray the behaviour patterns of user. The organization in which the data are positioned will provide a means for analysis of data. The transactions data done by customer can be used for categorizing for suggesting systems and to get high profit. So this is done by using KNN (K-nearest neighbour), Random forest (RF) and SVM (Support Vector Machine) classifier in this paper. These approaches are useful to recommend the best strategy planning to achieve decision making and enhance sales of products. Among all of them random forest is best method which has 99.86% accuracy.

**Keywords**—E-Commerce, Sales Performance, Business-to-Business (B2B), Machine Learning Approaches, Random Forest

## 1. INTRODUCTION

Basically, e-CRM is about attracting and retaining customers of economic value and repelling and disposing of those that are of economic importance[1]. E-commerce consumers communicate with web pages to conduct transactions. They are achieved using a customer interface that differs from the UI in the sense that mainly focuses on the role of delivering training in a cognitive fashion. It must

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therefore contain elements that draw tourists to linger and become regular customers and return to a company again.

It is not feasible or necessary, without internet and utilities, to presume an abstract nature of the e-commerce world. In the viewpoint of customer relationship management (CRM) a definition of consumer quality services / products may be different across various cultures for a regional e-commerce platform. In integration of CRM str, we understand the problems of e-business. In implementing CRM strategy in e-commerce around the world, we can see the problems facing e-business. The IT and IT-enabled e-Commerce environment provides both the front and back of the entire operation.

The usability of the customer-centered systems varies between organizations. Consumer satisfaction in the CRM domain is the product of the computer system's consumer efficiency and acceptability[2].

Sales research has mainly concentrate a lot on the sales management & the capabilities &profile of salespeople. The nature value creation in sales experiences among salespeople and customers is less understood .Real sales and actual sales experiences from B2B are crucial contexts in which value perceptions and ideas are generated and communicated through social interactions. This research focuses in genuine sales meetings on customer experiences. Salespersons and customers speak about the advantages, goods, facilities, references, procurement and distribution problems of a business, as well as the desires, preferences, concerns and choices of customers. Traditionally, salesmen from businesses to market sales and B2B sales seek to manipulate the decision of consumers by explaining how goods and services vary, Why one product better than another meets the needs of customers or why a customer be supposed to choose a specific company as a service providers[3].

Sales managers and salespeople reconcile the idea of effectiveness as regards sales success and evaluation has difficulty understanding and articulating it. No other problem triggered these uncertainties, confusion and divergence [4].

Data-driven decision-making is not an impulse, but a process that makes decisions based on data analysis. The high outputs of black box which is not transparent in machine learning (ML) models are RF, boosting, SVMs and NN (neural networking), which attain extensively improved analytical performance in compare of simple models that can be interpreted, for instance naive Bayes, decision trees, or decision rules [5]. This is one of the main causes why predictive ML models in the field wherever clarity & comprehension of decision is important poorly used and embraced.

Efficient business decision-making can be achieved with an effective sales prediction technique. Precise forecasts agree to company for maximize marketing expansion with highest profits generating rates. Machine learning approaches are most efficient in modification big amounts of data into help full knowledge for predicting costs &forecasting sales, it was the basis for resonance budget.

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Approaches to machine learning outlined in this research paper should provide an important framework for data alteration& decision taking. To be market experienced, companies need to equip themselves with new strategies to handle various forms of consumer activity by predicting attractive sales turn-over [6].

Techniques in machine learning could be extended to every restraint. Machine learning employs statistical data for solving various problems about classification & clustering. The ML techniques fell into 3 classes[7]. These are supervised, unmonitored & under semi-supervision. There are three machine learning techniques, for instance DT (Decision Tree), prediction & Gradient Boost Tree and Generalized Linear Model.
The machine learning technique for business sales decision& predicting techniques have discussed in the Section I and also an E-Commerce in B2B sales success has discussed. Section II outlines the study of numeral related works on sales forecasting. Section III also addresses the prediction analytics & methods on selling price. The performance assessments are reported for different predicting methods by use of machine learning techniques. Lastly, Section IV analyzes the results and ends with a review of the study findings and possible scope in Section V.

## 2. LITERATURE SURVEY

The McShane expansion of Lipschitz's function of reward is used for defining a new system by J.M. Calabuig et al. [8] marketplace for trading financial. A new metric that represents market trend are linear combination of the Euclidean norm and the geodesic distance. The McShane expansion can makes it possible for generating new successful states of the model that we call as "dreams". A new tool provided by a set of dreams for learning reinforcement which improves the system for simulating trends in market.

The aims of S. Mortensen et al. [9] toprojected method are of two-folding: 1) using mathematical modeling strategies for helping a destiny 500 papers & wrapping business codify what type of drives selling will successful2) creating a one model which forecast sales performance including rational level of precision. The expected long-run outcome was to allow a company to increase both top-line as well as bottom-line income by rising close selling rates, reduction selling cycle, & reducing manufacturing costs. The research team built several models to project winning propensities for individual revenue prospects, choosing the model with the greatest predictive capacity and the potential to produce knowledge that can be used as the foundation of a product for a customer. For do so, the panel used both ordered & unstructured data from Salesforce.com, the company's CRMS .They all are done experiments with number of methods consisting of binomial log it as well as another decision tree method which are gradient boosting &RF boosting. Particular characteristics of consumers, incentives, &inner reporting strategy has

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been established which encompass utmost impact upon selling performance. The preeminent model projected succeed tendency with 80 percent accuracy, 86 percent precision and 77 percent recall, which has proved that this projected method provide the enhancement over the previous accuracy of the sales forecasting.

C. Zhao et al. [10] Investigate decisions on the selling effort for a crowd funding market. For the built selling effort scenarios we devise three mathematical models, respectively. After comparing the best solutions under the three conditions, we evaluate the methods for maximum selling effort. We consider that: 1) the project creator and the developer have stronger incentives to offer sales efforts to improve crowd funding performance when the project's funding target is low; 2) the project creator likes to give sales efforts more opposed to the developer manager; 3) Unless the company has ample resources, both the project creator and the company will offer sales efforts; if not, it is best that the project creator offers sales efforts separately; 4) Sales efforts with positive interdependence are favored by both the platform and the project creator; 5) More potential customers attracted by the sales efforts of the platform would allow the project creator to increase their profits.

This paper adopted a latest big data modeling mechanism involving the study of B2B-based product / service cluster email archives. They have analyzed 621 k mails that were swap over 2009 to 2018. Yang Yang et al. [11] analyzed a certain number of discussion groups which were perceived to be proxy for interest to customers reflected in the products / services offered. Such groups & related discussed pattern was associated with sales as well economic results of the company, which demonstrated strong predictive ability. In doing so, they shown how readily accessible data, like mails that every businesses include, could utilized for support latest approaches of premature detection & tracking patterns in manufactured goods requirements, inform selling strategy.

A more consistent prediction in demanding to move consumer products fast are competitors for retailers and for producers, especially in fresh food, apparel and technology sectors. This investigative work highlights byElcio Tarallo et al. [12]the advantages of Learning approach in forecasting of sales to limited shelf-life & more-consumable goods, since it exceeds the precision point of conventional arithmetical methods in addition thus increases inventory management across the chain, decreasing stock-out levels at the point of sales, enhancing market accessibility as well as the productivity.

This research presents a novel paradigm of decision taking for stock market day-trading investments. The model was developed by Felipe Dias Paiva et al. [13]in this regard uses a fusion-based classifier method of machine learning, using the SVM approach, also portfolio selection approach of mean-variance (MV).Experimental evaluations of the platform were depending upon various

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resources as of the São Paulo Stock Exchange Index (Ibovespa). The best parameter performance sets (the in-sample phase) & testing (the out-of-sample phase) were selected using month-wise rolling window. The monthly windows consisted of every day rolling window, with novel classification algorithm training & portfolio optimization. A total 81 number of parameters setups have planned.

Experts also proposed heralding the fourth industrial revolution in the coming decades. The 4thindustrialized revolution would be motorized in digitization, ICT, ML, robot controls, & AI; also more decision-making would be transferred from humans to the machines .The resulting cultural revolutionize would have a most important effect on all research and activities related to personal sales and sales management. NiladriSyam and Arun Sharma [14] concentrate on only ML & AI and its effect on the management of personal marketing with sales. They analyze the effect depends upon the 7 steps of the selling procedure on a specific field of sales practice and analysis. Implications are built from theory and reality.

With an emergence of big data, the usage of the data-driven prediction system which is the way of driving improved sales results is becoming more and more popular, both in the B2C including B2B sectors. Though, the comparatively small amount of B2B transactions (as opposed to the amount of the B2C transactions), noisy data, & rapidly evolving business background present confront for successful analytical model. J. Yan et al. [15]suggest a coherent system for sales potential win propensity prediction based on machine learning, attempting to resolve these challenges. On the business-to-business market, we show the effectiveness of the projected program via data as of top 500 companies.

## 3. SYSTEM DESIGN AND IMPLEMENTATION

The aim is to assess whether there are differences in how researchers as well as practitioners interpret & identify salesperson performance metrics, and to present imminent into successful sales managing strategies in the fields like sales-person skills growth, target achievement, resource distribution, &CRM. Categorization and pattern mining from consumer data is important factors for supporting business and to make decisions. In business process identification of recently rising trends is important. Sales data from inventory indicates current marketing and it is used in predicting which has high potential for making decisions, planning the strategies and market competitiveness. Hence an approach is needed so that the customers, suppliers can be classified and proper win situation is created for the suppliers to gain more revenue along with providing correct recommendations for better customers.

### A. Proposed System

Classification and the identification of patterns from consumer data are very critical considerations for promoting company and making decisions.

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In business process it is important to recognize the newly emerging patterns. Inventory data distribution patterns are representative of consumer dynamics and can be used in forecasting that has tremendous potential for decision taking, strategic planning and market competition. In the proposed approach the transaction history of the users is taken into consideration and after taking the transaction history the products are divided into different kinds of stocks based on data mining algorithm and then finally the customers who have purchased low stock products are asked a series of questions to find the likeness of the products based on hypothesis of ease of use, customer satisfaction, shopping enjoyment.

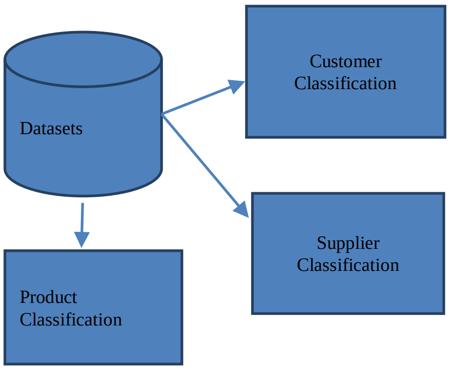


**Fig. 1 Data Module Categorization.**

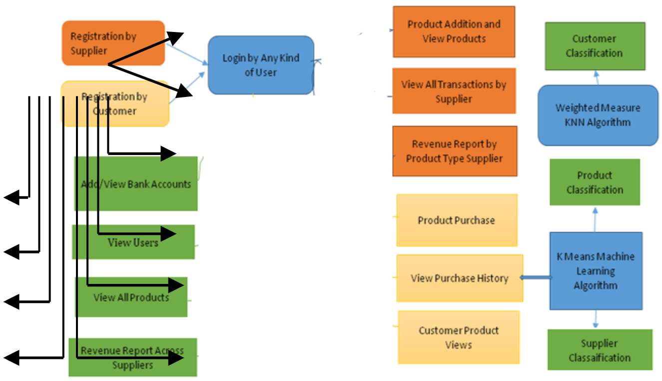


**Fig. 2 Classification Taxonomy.**

## Customer Classification

- **Register by Customer:** In this end user will provide username, password, email, phone number, city, state, country age and if any username does not exists and all other fields are provided in a proper fashion the end user is allowed to register with Login Type as 2.
- **Login for Customer:** In this the user will be provide the username and password. If invalid credentials are given user is not allowed to login otherwise user will login successful and based on type of user different functionalities can be executed by the end user.

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- **View Products for Each Type:** This functionality will retrieve all the products for each product type across the suppliers by providing the product id, product name, product description, product type, price and image of product.

- **Product Purchase:** This functionality will allow the customers to click on the product and purchase it by providing account number, ipin, delivery details and the completed the transaction by storing the order details.

**Supplier Classification**

The Supplier Classification is similar to that of customer classification. Instead of taking the customer level data the supplier level data is considered

- **Registration by Supplier:** In this the supplier will provide username, password, email, phone number, city, state, country age and if any username does not exists and all other fields are provided in a proper fashion the end user is allowed to register with Login Type as 3.
- **Login for Customer:** In this module the supplier will be provide the username and password. If invalid credentials are given user is not allowed to login otherwise user will login successful
- **Add Product:** This functionality allows the supplier to add the product by providing product name, product description, price, product type and internally the supplier name is stamped from the session.
- **View Products by Supplier:** This functionality will allow the supplier to view the products which have been uploaded by the supplier.
- **View Transactions by Supplier:** This functionality will allow the supplier to view all the transactions performed by the end users for the products provided by supplier.
- **View Revenue by Product Type:** This functionality will allow the supplier to view the total revenue by product type for various products provided by supplier.
- **View Revenue by Product Type for Specific Supplier:** This functionality will allow the supplier to view the total revenue and average revenue across product types for each specific supplier.
- **View Revenue across Suppliers:** This functionality will allow the admin to view the total revenue and average revenue across the suppliers.
- **Revenue Graph:** This functionality will provide the admin the graph of total and average revenue

**Product Classification**

The product Classification is similar to that of customer classification. Instead of taking the customer level data the product level data is considered

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- **View Users:** This module is used by the admin in order to view all the users who have registered into the application which can be customer/admin/supplier.
- **Add Bank Accounts:** This functionality will allow the admin to add bank account for testing purchase for the transactions.
- **Change Password:** This functionality will allow all types of users - administrator, customer and supplier - to change the password by giving old password, new password and confirmation password.
- **View All Products:** This functionality will show all the products across the suppliers by the admin.

## B. Architecture

### a) Client/Browser

The Admin can log in to the web server using the given user id and password to access the Collaborative filter Application.

### b) Web Server

It consists of the Collaborative filter application which allows the user to store, retrieve and query the data in data centre.

### c) MHE (Your Project)

It collects the data from the dataset and acts per the request made. It also generates report based on the analysis and prediction graphs.

### d) Helper Class/Business Logic

These are the additional classes that help the Collaborative filter application to interact with the data centre. (Example: JDBC, ODBC).

### e) Data Centre

Stores the patient related and doctor related information.

### f) Analysis and Prediction

The concept of heterogeneous graph and semi-supervised learning is used by admin to predict the risk in patient's health.

### g) Client/Browser

The Admin can log in to the web server using the given user id and password to access the Collaborative filter Application.

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### h) Web Server

It consists of the Collaborative filter application which allows the user to store, retrieve and query the data in data centre.

### i) MHE (Your Project)

It collects the data from the dataset and acts per the request made. It also generates report based on the analysis and prediction graphs.

### j) Helper Class/Business Logic

These are the additional classes that help the Collaborative filter application to interact with the data centre. (Example: JDBC, ODBC).

### k) Data Centre

Stores the patient related and doctor related information.

### l) Analysis and Prediction

The concept of heterogeneous graph and semi-supervised learning is used by admin to predict the risk in patient's health.

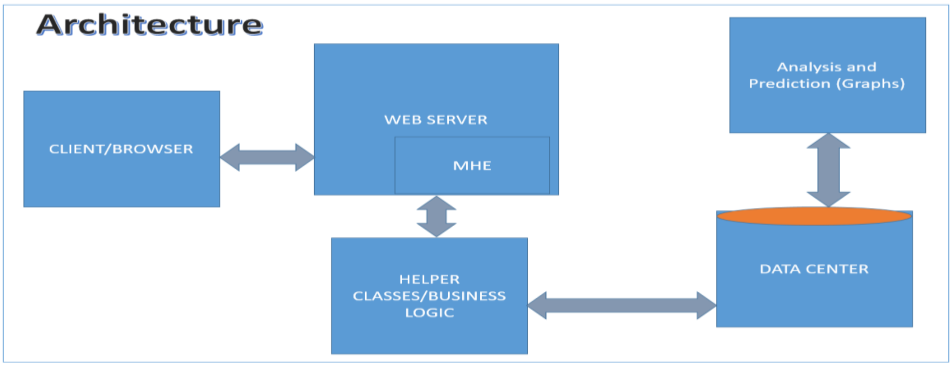


**Fig.3 Architecture Diagram.**

## C. Random Forest

Random forests [14] are an ensemble method for deciding on classification by voting on the outcomes of individual decision trees. An ensemble learner has two properties with excellent generalization accuracy, all module learner being highly accurate &module learners being highly diverse. Like another ensemble approaches for instance bagging & boosting, which is used to generate basis classifiers from the training data random samples, the random forest approach generate basis classifiers from an arbitrarily elected data subspaces .The randomly chosen subspaces improve the variety of simple classifiers acquired by the

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algorithm of a decision-tree. The significance assessment of features in the feature selection process is of particular importance. The most widely used score of importance for a given function in RF frameworks is a tree's mean error in the forest when the experimental values of given function are at random permutable in the out-of-bag samples. Selecting the features is most significant step in getting good performance for an RF model, particularly when dealt among HD data issues.

### *D. K-Nearest Neighbors Algorithm*

This concept of nearest neighboring technique is used by KNN algorithm. But in the case of KNN algorithm a fixed number of nearest neighbors is permitted to vote in the classification process of an unknown data tuple defined by k, where k is a +ve integer. When k=1 in that case the data tuple which is unknown is considered as the class that is near to the training data tuple.KNN is a lazy learner and is nonparametric. There is no express process of training in KNN. It only starts to work when it obtains an unknown classification tuple. The name of it is because of this working theory of KNN instance-based learner. K-Nearest Neighbor algorithm[17] works into various areas such as pattern identification, categorization of documents, accounting, agriculture, medicine etc.KNN algorithm can be used for classification as well as for regression. In classification the class parameter is of categorical form while it is a continuous variable in regression. For example, for locating the nearest k data points into the tuple that is unidentified, Minkowski distance, Euclidean distance and Manhattan distance are used. The Euclidean distance between two tuples of data P and Q is shown below:

$$\sqrt{\sum_{1\le i\le n} (p_i - q_i)^2} (1)$$

**Algorithm**

Input: Data set, k

Output: Categorized test tuples

Step 1: Accumulate the entire tuples for trained the network.

Step 2: For all concealed tuples designate labeled

a) Measure distance from it using equation number (1) for all training tuples.

b) Consider the closest tuples of training k to the unknown tuple.

c) Allocate of concealed tuples class that is mostly very common into nearest trained tuples k.

End for

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### E. Support-Vector machine

SVM is single and more necessary algorithm in machine learning which is implemented mainly for the problem of pattern-recognition. In machine learning a supervised method is SVM method here, based on examples of training set, each is classified as they belong to one category out of many, the training algorithm, SVM[15] creates a system which is used to predicts class for new example.

SVM have a greater potential to generalize the problem, which is the aim of statistical learning. Essentially, the key concept behind SVM is the design of an ideal hyper plane, which can be used for classification, for linearly separable patterns. The ideal hyper plane is a hyper plane selected from a set of hyper planes to identify patterns that optimize the margin value for hyper plane that is distance value from the hyper plane toward nearest point of all patterns. The main objective of SVM is to optimize the margin so that it can correctly identify the given patterns, i.e. the greater the margin size, the more accurately classifies the patterns. The eq. displayed below is the hyper-plane illustration:

Hyper plane, $pX + qY = R$(2)

## 4. RESULT AND DISSCUSSION

In this section we have defined software requirements and hardware requirements. These experiments have performed by using JAVA in Eclipse editor.

**TABLE I. SOFTWARE'S REQUIREMENTS**

| S. No | Name of parameter | Value of parameter |
|---|---|---|
| 1 | Simulation Platform | Java |
| 2 | Database for Routing Tables Backend | Mongo DB |
| 3 | Simulation Tool | Eclipse |
| 4 | Type of Sever | Web Server |
| 5 | Web Server Version | Tomcat 9.0 |
| 6 | Designing | Cascading Style Sheets |
| 7 | Front End Framework | Ext JS and Angular JS |

**TABLE II. HARDWARE'S REQUIREMENTS**

| S. No. | Parameters | Parameter Value |
|---|---|---|
| 1. | Random Access Memory | 8GB- 16GB |
| 2. | Hard Disk Drive | 120-160GB |

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### A. Dataset Description

Initially, we took large volume of dataset which is size of 97686. Here we used five dataset, which includes various attributes. These attributes are customer ID, country, product, quantity, total price and F-Score.

```
------------------------------
data set size 97606
------------------------------
top five data
```

Out[8]:

| | Unnamed: 0 | Unnamed: 0.1 | Invoice | category | Description | Quantity | InvoiceDate | Price | Customer ID | Country | product | total_price | fscore |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0 | 0 | 536365 | chocolates | WHITE HANGING HEART T-LIGHT HOLDER | 6 | 12/1/2010 8:26 | 2.55 | 17850.0 | United Kingdom | Kinder joy | 719.10 | 6.0 |
| 1 | 1 | 1 | 536365 | chocolates | WHITE METAL LANTERN | 6 | 12/1/2010 8:26 | 3.39 | 17850.0 | United Kingdom | Chuckles | 827.16 | 7.0 |
| 2 | 2 | 2 | 536365 | chocolates | CREAM CUPID HEARTS COAT HANGER | 8 | 12/1/2010 8:26 | 2.75 | 17850.0 | United Kingdom | Snickers | 602.25 | 6.0 |
| 3 | 3 | 3 | 536365 | chocolates | KNITTED UNION FLAG HOT WATER BOTTLE | 6 | 12/1/2010 8:26 | 3.39 | 17850.0 | United Kingdom | Dairy Milk | 759.36 | 7.0 |
| 4 | 4 | 4 | 536365 | chocolates | RED WOOLLY HOTTIE WHITE HEART. | 6 | 12/1/2010 8:26 | 3.39 | 17850.0 | United Kingdom | Choco Pie | 952.59 | 8.0 |



**Fig. 4 Data set information.**

### B. Screenshot of Results

```
After data preprocessing
```

Out[12]:

| | Unnamed: 0 | Unnamed: 0.1 | Invoice | category | Description | Quantity | InvoiceDate | Price | Customer ID | Country | product | total_price | fscore | product1 | category1 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0 | 0 | 536365 | chocolates | WHITE HANGING HEART T-LIGHT HOLDER | 6 | 12/1/2010 8:26 | 2.55 | 17850.0 | United Kingdom | Kinder joy | 719.10 | 6.0 | 29 | 7 |
| 1 | 1 | 1 | 536365 | chocolates | WHITE METAL LANTERN | 6 | 12/1/2010 8:26 | 3.39 | 17850.0 | United Kingdom | Chuckles | 827.16 | 7.0 | 9 | 7 |
| 2 | 2 | 2 | 536365 | chocolates | CREAM CUPID HEARTS COAT HANGER | 8 | 12/1/2010 8:26 | 2.75 | 17850.0 | United Kingdom | Snickers | 602.25 | 6.0 | 1 | 7 |
| 3 | 3 | 3 | 536365 | chocolates | KNITTED UNION FLAG HOT WATER BOTTLE | 6 | 12/1/2010 8:26 | 3.39 | 17850.0 | United Kingdom | Dairy Milk | 759.36 | 7.0 | 13 | 7 |
| 4 | 4 | 4 | 536365 | chocolates | RED WOOLLY HOTTIE WHITE HEART. | 6 | 12/1/2010 8:26 | 3.39 | 17850.0 | United Kingdom | Choco Pie | 952.59 | 8.0 | 21 | 7 |



**Fig. 5 After data prepossessing the dataset.**

In fig. 5 depicted the dataset after preprocessing. During this step we remove unused features and extract useful features.

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```
Testing accuracy on selected features in Randomforest: 99.862
confusion matrix
 [[2684    1    0    0    0    0    0    0    0    0]
 [   2 3263    2    0    0    0    0    0    0    0]
 [   0    3 2984    3    0    0    0    0    0    0]
 [   0    0    0 2207    0    0    0    0    0    0]
 [   0    0    0    1 1569    1    0    0    0    0]
 [   0    0    0    0    3 1342    0    0    0    0]
 [   0    0    0    0    0    0  976    2    0    0]
 [   0    0    0    0    0    0    0  778    0    0]
 [   0    0    0    0    0    0    0    0  622    5]
 [   0    0    0    0    0    0    0    0    4 3070]]
classification report
              precision    recall  f1-score   support

        1.0       1.00      1.00      1.00      2685
        2.0       1.00      1.00      1.00      3267
        3.0       1.00      1.00      1.00      2990
        4.0       1.00      1.00      1.00      2207
        5.0       1.00      1.00      1.00      1571
        6.0       1.00      1.00      1.00      1345
        7.0       1.00      1.00      1.00       978
        8.0       1.00      1.00      1.00       778
        9.0       0.99      0.99      0.99       627
       10.0       1.00      1.00      1.00      3074

  micro avg       1.00      1.00      1.00     19522
  macro avg       1.00      1.00      1.00     19522
```

**Fig. 6 Random Forest algorithm Accuracy and classification report and confusion matrix.**

Accuracy, confusion matrix and classification report for Random Forest algorithm depicted in fig. 6. The testing accuracy using random forest is 99.86% on selected features.

```
Testing accuracy on selected features in KNN: 71.166
confusion matrix
 [[2171  256  130   84   28    3    5    5    3    0]
 [ 302 2376  195  123   53   83   49   28   29   29]
 [ 107  316 2148   89   94   61   31   18    2  124]
 [  33  222  130 1502   56   75   45   16   22  106]
 [  14  116  160   33 1009   37   33   35   31  103]
 [   1   67   98  103   26  879   17   26   24  104]
 [   2   31   71   72   38   33  588    5   18  120]
 [   0   24   64   26   78   18   11  410    2  145]
 [   0    2   30   39   14   37    8    3  388  106]
 [   0   22   31  102  112  127  102   86   70 2422]]
classification report
              precision    recall  f1-score   support

        1.0       0.83      0.81      0.82      2685
        2.0       0.69      0.73      0.71      3267
        3.0       0.70      0.72      0.71      2990
        4.0       0.69      0.68      0.69      2207
        5.0       0.67      0.64      0.66      1571
        6.0       0.65      0.65      0.65      1345
        7.0       0.66      0.60      0.63       978
        8.0       0.65      0.53      0.58       778
        9.0       0.66      0.62      0.64       627
       10.0       0.74      0.79      0.76      3074

  micro avg       0.71      0.71      0.71     19522
  macro avg       0.69      0.68      0.68     19522
weighted avg       0.71      0.71      0.71     19522
```

**Fig. 7 KNN algorithm Accuracy and classification report and confusion matrix.**

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Accuracy, confusion matrix and classification report for KNN algorithm depicted in fig. 7. The testing accuracy using KNN is 71.17% on selected features.

```
Testing accuracy on selected features in SVM: 74.306
[[1919   91   25   10    1    0    0    0    0  639]
 [  43 2521   78   39    6    2    1    0    0  577]
 [  15   90 2346   16   19    9    3    0    0  492]
 [   6   75   23 1562    4   15    8    0    7  507]
 [   4   57   53    3  969    1    1    4    2  477]
 [   0   17   52   34    1  855    2    0    4  380]
 [   0   12   33   20    5    1  556    0    0  351]
 [   0    6   29   15   12    0    0  414    0  302]
 [   0    0    1   15    6    1    0    0  324  280]
 [   0    0    3    7    8   10    2    2    2 3040]]
              precision    recall  f1-score   support

         1.0       0.97      0.71      0.82      2685
         2.0       0.88      0.77      0.82      3267
         3.0       0.89      0.78      0.83      2990
         4.0       0.91      0.71      0.80      2207
         5.0       0.94      0.62      0.74      1571
         6.0       0.96      0.64      0.76      1345
         7.0       0.97      0.57      0.72       978
         8.0       0.99      0.53      0.69       778
         9.0       0.96      0.52      0.67       627
        10.0       0.43      0.99      0.60      3074

   micro avg       0.74      0.74      0.74     19522
   macro avg       0.89      0.68      0.75     19522
weighted avg       0.85      0.74      0.76     19522
```

**Fig. 8 SVM algorithm Accuracy and classification report and confusion matrix.**

Accuracy, confusion matrix and classification report for SVM algorithm depicted in fig. 8. The testing accuracy using SVM is 74.31% on selected features.

**TABLE II. COMPARISON AMONG VARIOUS METHODS IN TERMS OF ACCURACY**

| **Methods** | **Random Forest** | **KNN** | **SVM** |
|---|---|---|---|
| Accuracy | 99.86 | 71.17 | 74.31 |

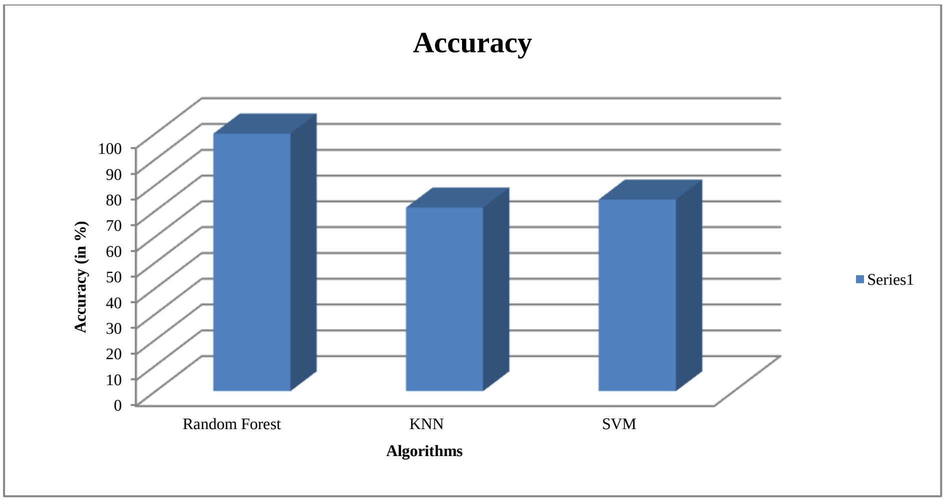


**Fig. 9 Accuracy comparison graph.**

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An Accuracy comparison graph for Random Forest, KNN and SVM classifier has depicted in fig. 9.

## 5. CONCLUSION

The purpose of the proposed model is to contribute for accepting the sales performance evaluation via creating an organizational structure in favor of the assessment of sales performance metrics on the basis of different performance parameters utilizedthrough researchers.Consequently, findings from both focus groups & comprehensively interviews with the sales managers & salespersons would be addressed by using established classification systems. This paper suggests a novel approach to coordinating forms of the performance metrics which is utilized, mixing flexibility by inside and outwardly focused indicators.The results show that there seems to be a difference between the performance metrics that analysts concentrate on and what is happening in the business field.

This research reveals the innovative application of the general interpretation approach for ML models to the dynamic real-world market issue of B2B revenue forecasting.The algorithms used here are random forest, KNN and SVM classifiers to assign attributes and achieve accurate results. Top five datasets are used for this purpose. From the random forest experimental tests, the KNN and SVM graders attained accuracy of 99.86 percent, 71.17 percent and 74.31 percent respectively.

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