

# A project report on

#### SALES ORDER MANAGEMENT APPLICATION

Submitted in partial fulfillment of the requirements for the Degree of

B. Tech in Computer Science Engineering

by

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under the guidance of

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also for their support in completing the project.

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operation and encouragement which helped me in completion of this project.

Signature: Aditya Chaudhary

**Aditya Chaudhary** 

#### **ABSTRACT**

Machine Learning and Artificial Intelligence, being the hottest trend today, is incredibly powerful for predictions or calculated suggestions based on large amounts of data.

As businesses from many industries have begun to rely more heavily on machines to do the heavy lifting of A/R processes, we are able to deliver more value to their customers.

Keeping a steady cash flow is one of the biggest if not the biggest problem that Small to Medium Enterprises deal with daily. Within the different types of c ash flow, Accounts Receivable (AR) classifies the balance of money that needs to be paid by the company's customers.

However, this often does not happen before the aforementioned date, meaning that the invoice is often paid late. Intervention requires resources and over-intervention could cause unwanted customer dissatisfaction. Knowing whether an invoice is going to be paid late can be vital information. Current methods of late payment prediction focus only on the history between the seller and the buyer and are unusable when this history is not present.

My project SALES ORDER MANAGEMENT APP is a tool or platform that tracks sales, orders, inventory, and fulfillment as well as enables the user to keep track of all these under one platform and make it easier for these companies to deal with Account Receivables.

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# CHAPTER 1 INTRODUCTION

#### 1.1 Purpose

The B2B world operates otherwise from the B2C or C2C world. Businesses work with different businesses on credit. Once a purchaser business orders product from the vendor business, the seller business problems an invoice for the same.

This invoice for the products contains numerous info like the details of the products purchased and once it ought to be paid. This is often better-known in accounting terminology as "Accounts Receivable".

Seller business interacts with numerous businesses and sells product to any or all of them at various times.

Hence, the vendor business has to keep track of the whole quantity it owes from all the buyers. This involves keeping track of all invoices from all the buyers. Every invoice can have numerous important fields sort of a payment due date, invoice date, invoice amount, baseline date etc.

#### 1.2 Objective

A Sales Order Management System is a computer software program that allows businesses to manage their Sales and inventory. Sales management systems help ensure more accurate inventory management, automatically entering new inventory into the system, tracking sales through different selling platforms, such as eBay and Amazon, and alerting you, the business owner, when your stock of a particular item drops low enough for a re-order.

A Sales Order Management system can also automate the Bill-to-cash process, beginning with the customer Bill through payment reconciliation, fulfillment, and shipment. Bill management software can work for both B2B and B2C businesses of any size.

Bill management software is also shareable, from the customer service team to the accounting team, the warehouse staff, and you, the business owner. The best kinds of inventory management systems also have a Sales Order management app, allowing you to manage your stock on the go and spot-check your business in real-time.

Effective Bill management improves the business workflow and increases the likelihood of repeat customers.

#### **CHAPTER 2**

#### BACKGROUND

#### 2.1 Sales Order Management System

Most order management software programs follow a 6-step system, relying on automation to help employees accurately process and fulfill customer orders. When used properly, order management software produces a seamless flow from entering invoices through after sales follow-up. The smoother the software runs, the faster you can fulfill orders, and the less likely your customer receives the wrong item or experiences the frustration of back orders.

#### 2.1.1. The order is placed

Your customer places an order through your third-party sales site, your own website, or over the phone with a live representative. Online, your customers will enter their details on a standardized form, with an option to have a securely saved preferred payment method.

To improve the sales process, make all fields of your online form mandatory so that you have all the necessary contact information for the customer up-front. This creates a customer profile and allows your order management system to track their purchase history, the volume of orders, and payment and delivery preferences. It also gives you their phone number and email address, should you need to follow up with service recovery.

The payment is processed, and then the order is sent to the warehouse once your software system approves the charges.

#### 2.1.2. Warehouse processing

Once the order arrives at the warehouse, it's checked by the intake team and the item or items are "picked" from the stock. Having a SKU and bar code for every item increases the accuracy of fulfillment and makes it easier for pickers to simply scan the item and add it to the order.

If there isn't enough of the item(s) in stock to fulfill an order, then a purchase order is automatically placed through the order management software. You and the warehouse manager will receive an alert that there may be a delay in fulfillment. Your customer may receive an automatic notification of the delay, and the customer service team can follow up with your customer.

#### 2.1.3. Reconciling the order

Next, the order is sent to the accounting department or preferably it should sync automatically with your cloud accounting software, where it's recorded in your A/R ledger. The sale is logged and a receipt sent to your client. Automating your sales ledgers makes it easier for auditing, inventory reconciliation, and end-of-year taxes.

#### 2.1.4. Shipping the order

Once the order is picked from the warehouse, your packing team will double-check for accuracy, again using the barcodes and SKU. Then, the order is packed carefully and shipped via a third-party delivery system. Your customer will receive a notice through the order management system that their order has shipped, along with a tracking number and estimated delivery time. As a store owner, you can also track the progress of shipped orders, which can be helpful if there are special needs orders, such as re-deliveries, VIP orders, or unusually large ones.

#### 2.1.5. Post-sales follow-up

Once the order arrives, the software should generate an automatic email to follow up, asking how they liked the items and ensuring that they received everything accurately. This email should include detailed instructions on how to reach customer service if there are any issues, taking the frustration out of guessing how to obtain a refund if needed.

Your customer service team oversees this process, thanking the customer for their business or working with them for a refund or replacement.

#### 2.1.6. Special order oversight

Another aspect of good OMS is the ability to flag a special order. This may be a return replacement or it could be a VIP order that includes a free thank-you gift or special coupon. When these orders are placed through the system, the software can flag them with a code, allowing you or your customer retention team to personally monitor the order for accuracy.

#### 2.2 Regression Analysis

In statistical modeling, regression analysis is a set of statistical processes for estimating the relationships between a dependent variable and one or more independent variables. The most common form of regression analysis is linear regression, in which one finds the line that most closely fits the data according to a specific mathematical criterion. For example, the method of ordinary least squares computes the unique line that minimizes the sum of squared differences between the true data and that line. For specific mathematical reasons, this allows the researcher to estimate the conditional expectation of the dependent variable when the independent variables take on a given set of values. Less common forms of regression use slightly different procedures to estimate alternative location

parameter estimate the conditional expectation across a broader collection of nonlinear models.

Regression analysis is primarily used for two conceptually distinct purposes. First, regression analysis is widely used for prediction and forecasting, where its use has substantial overlap with the field of machine learning. Second, in some situations regression analysis can be used to infer causal relationships between the independent and dependent variables. Importantly, regressions by themselves only reveal relationships between a dependent variable and a collection of independent variables in a fixed dataset. To use regressions for prediction or to infer causal relationships, respectively, a researcher must carefully justify why existing relationships have predictive power for a new context or why a relationship between two variables has a causal interpretation. The latter is especially important when researchers hope to estimate causal relationships using observational data.

#### 2.2.1 Linear Regression

In statistics, linear regression is a linear approach to modelling the relationship between a scalar response and one or more explanatory variables (also known as dependent and independent variables). The case of one explanatory variable is called simple linear regression; for more than one, the process is called multiple linear regression. This term is distinct from multivariate linear regression, where multiple correlated dependent variables are predicted, rather than a single scalar variable.

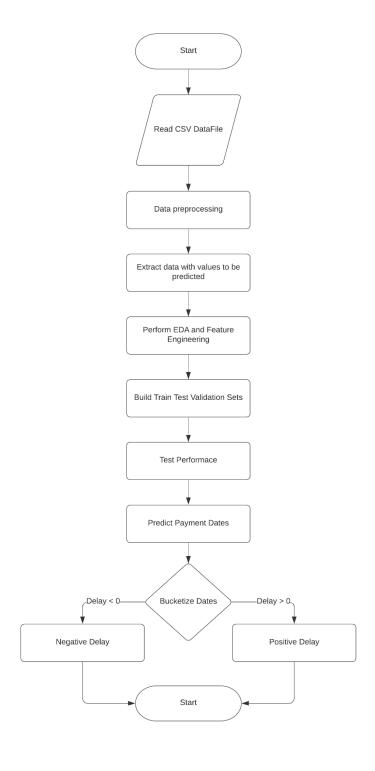
In linear regression, the relationships are modeled using linear predictor functions whose unknown model parameters are estimated from the data. Such models are called linear models. Most commonly, the conditional mean of the response given the values of the explanatory variables (or predictors) is assumed to be an affine function of those values; less commonly, the conditional median or some other quantile is used. Like all forms of regression analysis, linear regression focuses on the conditional probability distribution of the response given the values of the predictors, rather than on the joint probability distribution of all of these variables, which is the domain of multivariate analysis.

Linear regression was the first type of regression analysis to be studied rigorously, and to be used extensively in practical applications. This is because models which depend linearly on their unknown parameters are easier to fit than models which are non-linearly related to their parameters and because the statistical properties of the resulting estimators are easier to determine.

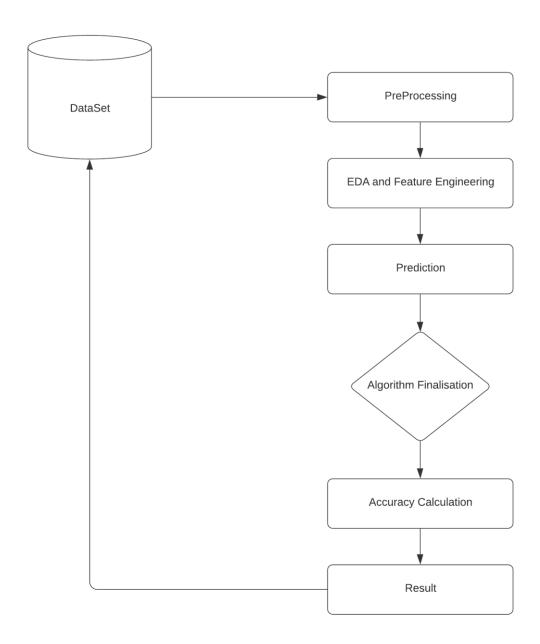
#### **CHAPTER 3**

# PROJECT ANALYSIS/ PROJECT IMPLEMENTATION

# 3.1 Project Flow Chart



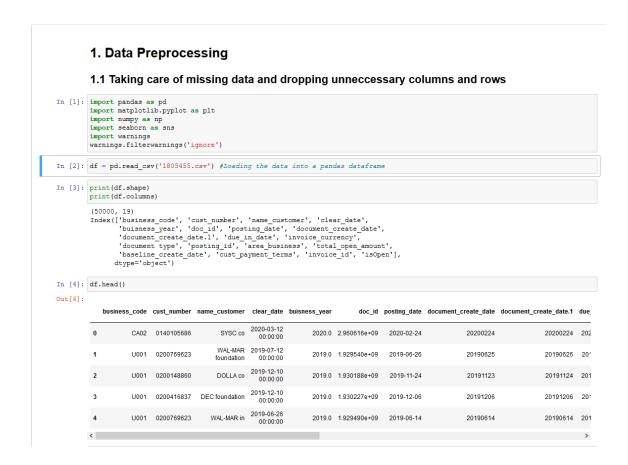
# 3.2 Data Flow Diagram



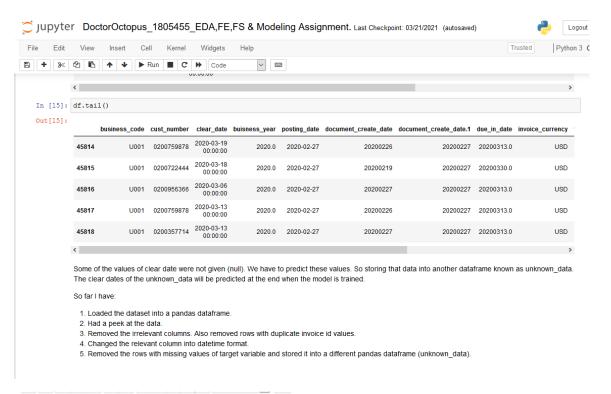
# 3.3 Project Implementation

#### 3.3.1 Machine Learning Implementation

#### 3.3.1.1 Data Preprocessing



```
In [5]: df.isna().sum()
  Out[5]: business code
                                                 0
            cust_number
            name_customer
                                              4176
            clear date
            buisness_year
            doc id
            posting_date
            document_create_date
            document_create_date.1
            due_in_date
            invoice_currency
document type
posting_id
            area_business
total_open_amount
                                            50000
            baseline create date
            cust_payment_terms
            invoice_id
            isOpen
dtype: int64
 In [6]: df.sort_values(by = 'document_create_date.1', inplace = True)
df.reset_index(inplace = True, drop = True)
 In [7]: unknown data = df[df.clear date.isnull()]
           df = df[df.clear_date.notnull()]
print(unknown data.shape)
            print(df.shape)
            (4176, 19)
(45824, 19)
 In [8]: df.drop(['area_business', 'name_customer'], axis = 1, inplace = True)
            Since all values of area business columns are NANs, we can drop this column. Also, we have a unique customer id for each customer. So we can drop this as
 In [9]: df.drop(df[df.total_open_amount < 0].index, inplace = True)</pre>
In [10]: print(df.doc_id.unique().shape)
            print(df.invoice_id.unique().shape)
           print(df.shape)
In [10]: print(df.doc_id.unique().shape)
    print(df.invoice_id.unique().shape)
           print(df.shape)
            (45824,)
            (45819,)
            (45824, 17)
            Here we observe that there is a unique doc_id for each entry so we can safely discard this column. Invoice id is also supposed to be unique. But, we can see
            that there are duplicate values here and they should be removed.
In [11]:
    df = df.drop_duplicates(subset = 'invoice_id').reset_index(drop = True)
    df.drop(['doo_id','invoice_id'], axis = 1, inplace = True)
In [12]: print(df['document type'].value_counts())
    print(df.posting_id.unique())
    print(df.isOpen.unique())
                 45818
            Name: document type, dtype: int64
           [1.]
[0]
            We can drop the columns 'posting' id' and 'isOpen' because they take only one unique value. There is only one X2 document type and rest are RV. So we
           need to drop the row with X2 type document and then drop the column 'document type' altogether
In [13]: df.drop(df[df['document type'] == 'X2'].index, inplace = True)
df.drop(['document type', 'posting_id', 'isOpen'], axis = 1, inplace = True)
In [14]: df.head()
Out[14]:
               business_code cust_number clear_date buisness_year posting_date document_create_date document_create_date.1 due_in_date invoice_currency total
                        U001 0200769623 2019-01-09
             0
                                                                2019.0 2018-12-30
                                                                                                  20181229
                                                                                                                          20181230 20190114.0
                                                                                                                                                             USD
                        U001 0200744019 2019-01-18
             1
                                                                2019.0 2018-12-30
                                                                                                  20181229
                                                                                                                          20181230 20190114.0
                                                                                                                                                             USD
                        U001 0200704045 2019-01-14
             2
                                                                2019.0 2018-12-30
                                                                                                  20181230
                                                                                                                          20181230 20190114.0
                                                                                                                                                             USD
                        U001 0200759878 2019-01-15
             3
                                                                2019.0 2018-12-30
                                                                                                  20181229
                                                                                                                          20181230 20190114.0
                                                                                                                                                             USD
                        U001 0200418007 2019-01-15
                                                                2019.0 2018-12-30
                                                                                                  20181231
                                                                                                                          20181230 20190114.0
                                                                                                                                                             USD
```



#### 1.2 Categorical data

```
In [16]: print(df.invoice_currency.value_counts())
           print(df.business_code.value_counts())
print(df.cust_payment_terms.value_counts())
print(df.cust_number.value_counts())
           print(df.buisness_year.value_counts())
                    42141
3677
           USD
           CAD
           Name: invoice_currency, dtype: int64
           U001
           CA02
                      3677
           U013
                        593
           U002
                       141
           U005
           Name: business_code, dtype: int64
           NAA8
                     18435
           NAH4
                     12061
                      3587
           NAC6
                      1530
           NAM4
                      1241
                     . . .
           NATW
           NAUX
           NANC
           NATM
           Name: cust_
0200769623
                  cust_payment_terms, Length: 74, dtype: int64
           0200726979
                             1715
           0200762301
           0200759878
                             1215
           0200794332
           100008001
0100014735
           0200092114
           0200958768
           Name: cust number, Length: 1411, dtype: int64 2019.0 39871
           2020.0
                         5947
           Name: buisness_year, dtype: int64
           Here we can conclude that
             1. Two types of currencies are used. We should convert all CAD amounts to USD and then label encode invoice_currency column
```

- 2. We can one hot encode the business code column.
- 3. We can label encode the cust\_payment terms column.
- 4. We can label encode the cust\_number column.

```
In [17]: conv_rate_2019 = 0.753598
    conv_rate_2020 = 0.74652
    conv_rate_2021 = 0.786105
if(data.loc[index,'invoice_currency'] == 'CAD'):
    if(data.loc[index,'buisness_year'] == 2019):
                                                                                                    data.loc[index, 'total_open_amount'] = data.iloc[index].total_open_amount * conv_rate_2019 if(data.loc[index, 'buisness_year'] == 2020): data.loc[index, 'total_open_amount'] = data.iloc[index].total_open_amount * conv_rate_2020 if(data.loc[index, 'buisness_year'] == 2021): data.loc[index, 'total_open_amount'] = data.iloc[index].total_open_amount * conv_rate_2021 data.loc[index, 'total_open_amount'] = data.iloc[index].total_open_amount * conv_rate_2021 data.loc[index].total_open_amount * conv_rate_2021 data.loc[
 In [19]: df = currency_convertor(df)
 In [20]: from sklearn.preprocessing import LabelEncoder
                                             le 1 = LabelEncoder()
                                            le_2 = LabelEncoder()
le_3 = LabelEncoder()
                                             df['cust_payment_terms_1'] = df['cust_payment_terms']  # A separate column for EDA. Will be dropped in training
                                            df['invoice_currency'] = le_1.fit_transform(df['invoice_currency'])
df['cust_payment_terms'] = le_2.fit_transform(df['cust_payment_terms'])
df['cust_number'] = le_3.fit_transform(df['cust_number'])
 Out[20]:
                                                         business_code cust_number clear_date buisness_year posting_date document_create_date document_create_date.1 due_in_date invoice_current_create_date.2 document_create_date.3 document_c
                                                                                                                                                    868 2019-01-09
00:00:00
                                                                                                                                                                                                                                           2019.0 2018-12-30
                                                                                                                                                                                                                                                                                                                                                                      20181229
                                                                                                                                                                                                                                                                                                                                                                                                                                                               20181230 20190114.0
                                                                                                                                                    814 2019-01-18
00:00:00
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                                                                                                                                                                                                                                           2019.0 2018-12-30
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                                                                                                                                                                                                                                                                                                                                                                                                                                                               20181230 20190114.0
                                                                                                                                                    714 2019-01-14
00:00:00
                                                                                              U001
                                                                                                                                                                                                                                            2019.0 2018-12-30
                                                                                                                                                                                                                                                                                                                                                                       20181230
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                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                         20190114.0
                                                                                                                                                    846 2019-01-15
00:00:00
                                                3
                                                                                              U001
                                                                                                                                                                                                                                            2019.0 2018-12-30
                                                                                                                                                                                                                                                                                                                                                                       20181229
                                                                                                                                                                                                                                                                                                                                                                                                                                                               20181230
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                        20190114.0
                                                                                                                                                    596 2019-01-15
00:00:00
                                                                                              U001
                                                                                                                                                                                                                                           2019.0 2018-12-30
                                                                                                                                                                                                                                                                                                                                                                        20181231
                                                                                                                                                                                                                                                                                                                                                                                                                                                               20181230 20190114.0
 In [21]: df['business code 1'] = df['business code']
                                            from sklearn.compose import ColumnTransformer from sklearn.preprocessing import OneHotEncoder
                                            ct = ColumnTransformer(transformers=[('encoder',OneHotEncoder(),[0])], remainder= 'passthrough')
df = np.array(ct.fit_transform(df))
```

#### 1.3 Preprocessing of date time columns

```
In [23]: df['clear_date'] = pd.to_datetime(df['clear_date'])
    df['posting_date'] = pd.to_datetime(df['posting_date'])
    df['document_create_date.i'] = pd.to_datetime(df['document_create_date.1'], errors='ignore', format='%Y%m%d')
    df['due_in_date'] = pd.to_datetime(df['due_in_date'], format='%Y%m%d')
    df['baseline_create_date'] = pd.to_datetime(df['baseline_create_date'], format = '%Y%m%d')
In [24]: df.drop('document_create_date', axis = 1, inplace = True)
In [25]: document_create_date_1 = df['document_create_date.1'] df['delay'] = (df['clear_date'] - df['due_in_date']).dt.days #This will be the dependent variable which the model will predict.
                df['month of due dependent variable valor the model viil predict.

df['month of due date'] = df['due in date'] d.t.month

df['clear date'] = (df['clear date'] - document create_date 1).dt.days

df['posting_date'] = (df['posting_date'] - document_create_date_1).dt.days

df['baseline create_date'] = (df['baseline_create_date'] - document create_date_3).dt.days

df['due_in_days'] = (df['due_in_date'] - document_create_date_1).dt.days

df.head()
                 df.head()
Out[25]:
                     0 1 2 3 4 5 cust_number clear_date buisness_year posting_date ... due_in_date invoice_currency total_open_amount baseline_create_date
                  0 0 1 0 0 0 0 868 10 2019 0 ... 2019-01-14 1 1078.89
                                                                                                                                                                                                                              0
                                                      814 19
                                                                                     2019
                                                                                                                                                                                         12839.5
                  1 0 1 0 0 0 0
                                                                                                                      0 ... 2019-01-14
                                                                                                                                                                                                                               0
                  2 0 1 0 0 0 0 714 15 2019 0 ... 2019-01-14 1
                                                                                                                                                                                         106472
                  3 0 1 0 0 0 0
                                                    846 16 2019
                                                                                                                     0 ... 2019-01-14
                                                                                                                                                                                         51464.6
                  4 0 1 0 0 0 0 596 16 2019 0 ... 2019-01-14
                                                                                                                                                                                          49711.3
                 5 rows × 21 columns
                 <
                 Now we need to remove the anomalies.
In [26]:
df.drop(df[df.clear_date < df.baseline_create_date].index, inplace = True)
df.drop(df[df.due_in_days <= df.baseline_create_date].index, inplace = True)
df.drop(df[df.due_in_days <= 0].index, inplace = True)
df.drop(df[df.baseline_create_date < 0].index, inplace = True)
df.drop(df[df.clear_date <= 0].index, inplace = True)
df.reset_index(inplace = True, drop = True)</pre>
In [27]: print(df['posting_date'].value_counts())
                     43021
                 Name: posting_date, dtype: int64
```

```
In [29]: df.dtypes
                                                                                                                                                                                                                                                                    object
                                                                                                                                                                                                                                                                     object
                                                                  cust number
                                                                                                                                                                                                                                                                    object
                                                                     clear_date
                                                                                                                                                                                                                                                                        int64
                                                                 datetime64[ns]
due in date
tinvoice_currency
total_open_amount
baseline_create_date
baseline_create_date.1
baseline_create_date.2
baseline_create_date
                                                                                                                                                                                                                  object
object
object
                                                                 cust_payment_terms
cust_payment_terms_1
business_code_1
                                                                  delay
                                                                                                                                                                                                                                                                        int64
                                                                                                                                                                                                                                                           int64
int64
int64
                                                                  month_of_due_date
                                                                  due_in_days
dtype: object
                In [30]: df['0'] = df['0'].astype(int)
                                                                 df['1'] = df['1'].astype(int)
df['2'] = df['2'].astype(int)
                                                                df('2'] = df('2'].astype(int)
df('3'] = df('3'].astype(int)
df('4'] = df('4'].astype(int)
df('4'] = df('4'].astype(int)
df('cust number'] = df('cust number'].astype(int)
df('interval number'] = df('buisness year'].astype(int)
df('total_open_amount'] = df('total_open_amount').astype(int)
df('invoice_currency'] = df('invoice_currency').astype(int)
df('cust_payment_terms') = df('cust_payment_terms').astype(int)
df('total_open_amount') = df('cust_payment_terms').astype(int)
                                                                  df.dtypes
              Out[30]: 0
                                                                                                                                                                                                                                                                        int32
int32
                                                                                                                                                                                                                                                                        int32
                                                                                                                                                                                                                                                                          int32
                                                                                                                                                                                                                                                                          int32
                                                                 cust_number
clear_date
                                                                                                                                                                                                                                                                        int32
                                                                                                                                                                                                                                                                        int64
                                                                 buisness_year buisness_year document_create_date.1 datetime64[ns] invoice_currency int32
                                                                                                                                                                                                                  int32
                                                                month_of_due_date
                                                                                                                                                                                                                                                                       int64
                                                                  due_in_days
dtype: object
```

#### 3.3.1.2 Splitting of data into Train, Test and Validation Sets

```
In [31]: df.shape
Out[31]: (43021, 20)

In [32]: from sklearn.model_selection import train_test_split training_set, test_set = train_test_split(df, test_size= 0.3, shuffle = False) val, test = train_test_split(test_set, test_size= 0.5, shuffle = False)

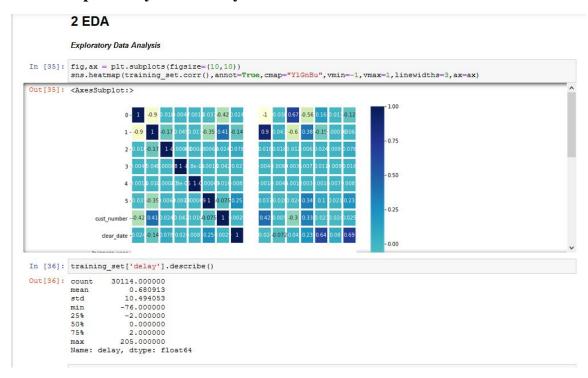
In [33]: print(training_set.shape) print(val.shape) print(val.shape) print(test.shape)

(30114, 20) (6453, 20) (6454, 20)

In [34]: training_set.columns

Out[34]: Index(['0', '1', '2', '3', '4', '5', 'cust_number', 'clear_date', 'buisness_year', 'document_create_date.1', 'due_in_date', 'invoice_currency', 'total_open_amount', 'baseline_create_date', 'cust_payment_terms_1', 'cust_payment_terms_1', 'business_code_1', 'delay', 'month_of_due_date', 'due_in_days'], dtype='object')
```

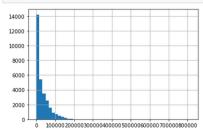
# 3.3.1.3 Exploratory Data Analysis





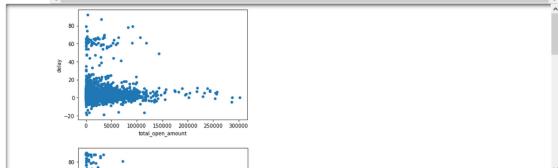
There is no clear cut effect of due date and baseline create on delay. There are delays in short term invoices as well as long term invoices. Thus, due date and baseline create date are not important features to understand delay. These column will be dropped during training and predicting. Month of due date has some effect on delay and will be used in the model

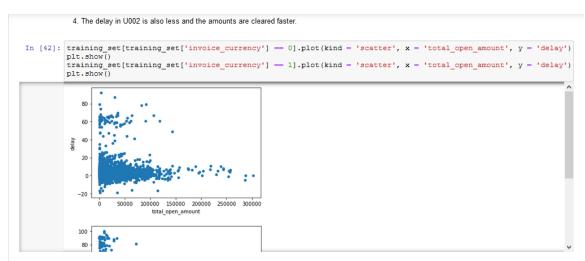
```
In [40]: training_set['total_open_amount'].hist(bins = 50)
plt.show()
```



We can infer that a large number of invoices have a small total open amount. As total open amount increases, number of data points decrease.

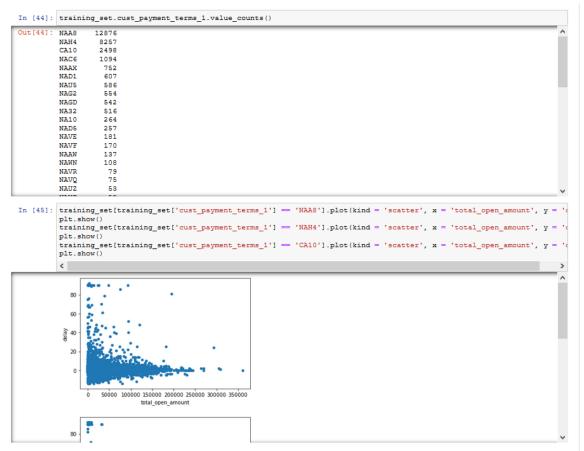
```
In [41]: training_set[training_set['business_code_1'] == 'CA02'].plot(kind = 'scatter', x = 'total_open_amount', y = 'del_plt.show()
    training_set[training_set['business_code_1'] == 'U001'].plot(kind = 'scatter', x = 'total_open_amount', y = 'del_plt.show()
    training_set[training_set['business_code_1'] == 'U013'].plot(kind = 'scatter', x = 'total_open_amount', y = 'del_plt.show()
    training_set[training_set['business_code_1'] == 'U002'].plot(kind = 'scatter', x = 'total_open_amount', y = 'del_plt.show()
```





The invoice currency plot for CAD is the same as the plot for business type CA02. Hence the effect of currency is incorporated in the business type column. Hence we will drop this column in training the model

Generally, baseline create date is on the same day as document create date. Thus the payment window generally opens on the same day on which the document is created.



There are many types of cust payment terms which have a very few data points. Hence it is not enough to be a relevant feature in the model. Also if we look at the curves of delay vs amount for the top three most abundant cust payment terms, we find that there is not much difference in the variance, max and min values of delay. Hence we should drop this column as well while training the model and predicting the outputs.

Hence by EDA we can conclude the important features which we need to train the model.

- 1. Business Code
- 2. Month of due date
- Total Open Amount

#### 3.3.1.4 Splitting data into dependent and independent variables.

#### 3.3.1.5 Feature Scaling

#### 4 Feature Scaling (not required for Tree based models)

We are using Standard Scaler for Feature Scaling.

```
In [49]:
    from sklearn.preprocessing import StandardScaler
    sc_X_train = StandardScaler()
    sc_Y_train = StandardScaler()
    X_train = StandardScaler()
    X_train_scaled = sc_X_train.fit_transform(training_set)
    Y_train_scaled = sc_Y_train.fit_transform(Y_train.reshape(-1,1))
```

#### 3.3.1.5 Training with Multiple Linear Regression (MLR)

#### 5. Training different models and checking RMSE.

```
In [50]: from sklearn.metrics import mean_squared_error
           5.1 Multiple Linear Regression
In [51]: from sklearn.linear_model import LinearRegression
    regressor_linear = LinearRegression()
           regressor_linear.fit(X_train_scaled, Y_train_scaled)
Out[51]: LinearRegression()
           Y_pred_val1_linear is the variable to store our predictions for val set Since linear model takes in standardised inputs, we use so_x_train to first
           standardise the val set (innermost bracket). Then we use the predict functions to predict the delays.. but the output is standardised.. to bring it back to
           original scale we use inverse_transform function... And we need to inverse transform the standardised delay predictions so we use sx_y_train object's
           inverse transform method.
           The next 2 lines are a way to print our predictions and original delays side by side
In [52]: Y_pred_val_linear = sc_Y_train.inverse_transform(regressor_linear.predict(sc_X_train.transform(val)))
           np.set printoptions(precision=2)
           print(np.concatenate((Y_pred_val_linear.reshape(len(Y_pred_val_linear),1), Y_val.reshape(len(Y_val),1)),1))
             [-0.24 1.
             [-0.38 0. ]
            [-0.43 3. ]
[-0.35 -4. ]]
In [53]: print(np.sqrt(mean_squared_error(Y_val, Y_pred_val_linear))) #RMSE on val set
           5.319850060842998
In [54]: Y pred_test_linear = sc Y_train.inverse_transform(regressor_linear.predict(sc_X_train.transform(test)))
print(np.sqrt(mean_squared_error(Y_test, Y_pred_test_linear))) #RMSE on test set
           9.06535461390192
In [55]: Y_pred_test_linear.max()
Out[55]: 9.59997193434786
```

This model is greatly overfitting on our training set

#### 3.3.1.6 Training with Support Vector Regression (SVR)

Poor performance on test set. Also the range of predictions is low. Max delay is just 10 days, which is very unlikely to occur.

#### **3.3.1.7** Training with Decision Tree Regression ( D-Tree Regression )

#### 5.3 Decision Tree Regression

```
In [61]: from sklearn.tree import DecisionTreeRegressor
    regressor_dt = DecisionTreeRegressor (random_state = 0)
    regressor_dt.fit(training_st, Y_train)

Out[61]: DecisionTreeRegressor (random_state=0)

In [62]: Y_pred_val_dt = regressor_dt.predict(val)
    print(np.sqrt(mean_squared_error(Y_val, Y_pred_val_dt))) #RMSE on val set

17.451042605757483
```

As, the validation set is only giving such high RMSE, the test will be worse, so we are discarding this method and not even going to bother using the test set.

#### **3.3.1.8** Training with Random Forest Regression (RF-Regression)

```
5.5 Random Forest Regression

In [63]: from sklearn.ensemble import RandomForestRegressor regressor_rf = RandomForestRegressor (n_estimators = 30, random_state = 0) regressor_rf.fit(training_set, Y_train)

Out[63]: RandomForestRegressor(n_estimators=30, random_state=0)

In [64]: Y_pred_val_rf = regressor_rf.predict(val) print(np.sqrt(mean_squared_error(Y_val,Y_pred_val_rf))) #RMSE on val set

12.041050951044634

In [65]: Y_pred_test_rf = regressor_rf.predict(test) print(np.sqrt(mean_squared_error(Y_test,Y_pred_test_rf))) #RMSE on test set

10.903386093707242

In [66]: Y_pred_test_rf.max() #Here, ve are checking the max value ve got from test.

Out[66]: 67.2666666666667

Conclusion: I am selecting Random Forest Regression Model to predict the unknown data.
```

<u>Conclusion</u>: Since <u>Random Forest Regression</u> algorithm, gave the best scores we will be using this algorithm to predict the payment dates for our unknown data.

# 3.3.1.10 Prediction of our unknown data using Random Forest Regression

```
6. Predicting the Unknown Data.
In [67]: unknown_data.columns
dtype='object')
In [68]: unknown data 1 = unknown data.copy()
In [70]: unknown_data_1['business_code_1'] = unknown_data_1['business_code']
      In [71]: unknown_data_1.reset_index(inplace= True, drop= True)
      unknown_data_1 = currency_convertor(unknown_data_1)
In [72]: unknown_data_1['due_in_date'] = pd.to_datetime(unknown_data_1['due_in_date'],format='%Y%m%d') unknown_data_1['month_of_due_date'] = unknown_data_1['due_in_date'].dt.month
unknown_data_1.columns
Out[73]: Index(['0', '1', '2', '3', '4', '5', 'total_open_amount', 'month_of_due_date'], dtype='object')
In [74]: predictions = regressor_rf.predict(unknown_data_1)
       In [75]: unknown_data['due_in_date'] = pd.to_datetime(unknown_data['due_in_date'],format='%Y%m%d')
In [76]: unknown_data.reset_index(inplace = True, drop = True)
In [74]: predictions = regressor rf.predict(unknown data 1)
      predictions = np.round(predictions) #rounding off our predicted delays, as days can not be decimal values.
In [75]: unknown_data['due_in_date'] = pd.to_datetime(unknown_data['due_in_date'],format='%Y%m%d')
In [76]: unknown_data.reset_index(inplace = True, drop = True)
In [77]: for index in unknown_data.index: #calculation of our clear date by iterating and adding predicted delay to due dates.
      unknown_data.loc[index, 'clear_date'] = (unknown_data.iloc[index].due_in_date + pd.Timedelta(predictions[index])).date()
In [78]: unknown_data['bucket'] = predictions
```

#### 3.3.1.11 Bucketization of final predicted data

```
Here we are bucketizing our output based on our bucketing conditions.
                Buckets Summary
                Cleared before due date [ < 0 days]
                Bucket 1 [0-15 days]
                Bucket 2 [16-30 days]
                Bucket 3 [31-45 days]
                Bucket 4 [46-60 days]
                Bucket 5 [Greater than 60 days]
In [79]: for index in unknown_data.index:
                      index in unknown_data.index:
if unknown_data.loc[index,'bucket'] < 0:
    unknown_data.loc[index, 'bucket'] = 'Cleared before due date
elif unknown_data.loc[index, 'bucket'] <=15:
    unknown_data.loc[index,'bucket'] <= 30:
    unknown_data.loc[index,'bucket'] <= 30:
    unknown_data.loc[index,'bucket'] = 'Bucket 2 [16-30 days]
elif unknown_data.loc[index,'bucket'] <= 45:
    unknown_data.loc[index,'bucket'] == Bucket 3 [31-45 days]
elif unknown_data.loc[index,'bucket'] == 60:
    unknown_data.loc[index,'bucket'] == Bucket 4 [46-60 days]
else:</pre>
                             unknown_data.loc[index,'bucket'] = 'Bucket 5 [Greater than 60 days] :'
                Final Output with Buckets.
In [80]: print('
                                                                                          Number of invoices')
                unknown_data.bucket.value_counts()
                                                                                   Number of invoices
Out[80]: Bucket 1 [0-15 days]
                                                                                      2462
               Bucket 1 [0-15 days]
Cleared before due date
Bucket 2 [16-30 days]
Bucket 3 [31-45 days]
                                                                                       1622
52
19
                Bucket 4 [46-60 days] :
Bucket 5 [Greater than 60 days] :
                Name: bucket, dtype: int64
                The output here is sorted because .value_counts() returns by the highest frequency
                Final Output with Buckets.
In [80]: print('
                unknown_data.bucket.value_counts()
                           Buckets
                                                                             Number of invoices
Out[80]: Bucket 1 [0-15 days]
                                                                                    2462
               Bucket 1 [0-15 days] :
Cleared before due date :
Bucket 2 [16-30 days] :
Bucket 3 [31-45 days] :
Bucket 4 [46-60 days] :
Bucket 5 [Greater than 60 days] :
                                                                                     1622
                                                                                         19
                                                                                         18
                Name: bucket, dtype: int64
                The output here is sorted because .value_counts() returns by the highest frequency
                Submitted by : Aditya Chaudhary
                Roll Number : 1805455
                High Radius Tech Track Machine Learning Project.
```

# 3.3.2 Java Backend Implementation

# 3.3.2.1 Java POJO Class implementation and JDBC Registration

#### 3.3.2.2 Java Servlets

#### 3.3.2.2.1 Data Add Servlet

```
Description of the Content of the Co
```

```
printEnter out = response_getWriter(); //do)ect of response to send.

PrintEnter out = response_getWriter(); //do)ect of response to send.

String Base = request, offermatter("nom");

Simplesterformat formatter = rew SimpleSteformat(TEE Nom do yyyy Nilmonis 222", Locale.EXGLISH);

try {
    date = formatter_para(request_optParameter("cist"));
    cation (ParaeEccoption o) {
        a.crimitalseTrace();
        String India = request_optParameter("cist"));
        String India = request_optParameter("cist"));
        String India = request_optParameter("cist"));
        String India = request_optParameter("cist"));
        String India = request_optParameter("cist");
        String India India = request_optParameter("cist");
        String India = request_optParame
```

```
private visic Andobtalstring Name, Date date String invid.String CostNum.String Annount.String motes.String docid) {
    final String Book, Private * Cosm.mass.Lis.jobs.Chriser;
    final String Book * Prost:
    // Prost
```

```
stat.close();
}catch(SQLException se2){
};
try{
if(come!nut))
com.close();
}catch(SQLException se)/
se.printStackTrace();
}
}

BouppressWarnings('deprecation')
private static String change_date(Date date){
String Finalcate = ""
Finalcate * "(ste.getVen(')=588);
String Indiant = ""
Finalcate * "(ste.getVen(')=588);
String south * integer toString(date.getNorth()+1);
if(conth.length() * 1)
Finalcate * "(ste.getVen(')=588);
String day * Integer toString(date.getDate());
if(conth.length() * 1)
Finalcate * "";
Finalcate
```

#### 3.3.2.2.2 Data Delete Servlet

```
| Second | S
```

#### 3.3.2.2.3 Data Edit Servlet

```
print vaid stitati(tring) index, strong amount, String and * "STRING amount, String amount, String and * "STRING amount, String amount
```

```
}
}

protected Void doPost(HttpServletRequest request, HttpServletResponse response) throws ServletException, IOException {
    doGet(request, response);
}
```

#### 3.3.2.2.4 Data Fetch Servlet

```
### Services |
### Se
```

```
### Action of the property of
```

```
//Converting to 250m using 650m.

Seem goom = new Goom();
String data = goom.noison(fetch)Mgdta(Pageld.value));
response.setContertyGe_Sepilcation(/spon*);
response.setContertyGe_Sepilcation(/spon*);
response.setContertyGe_Sepilcation(/spon*);
system.out.printin(data);
out.flush();
}
}
```

#### 3.3.2.2.5 Data Search Servlet

```
Demokratic (Tabilization)

Smolic (iss Databaseron ortions Studenty ( )

policis databaseron ( )

Demokratic (Tabilizations ( )

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```

```
Arregulations of the defailst * now Arregulations of the community of the
```

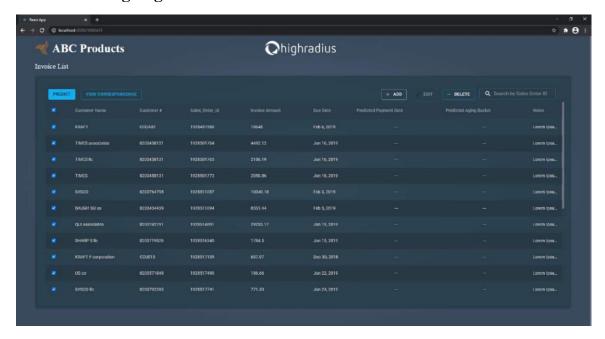
```
}
}
return dataList:
}

protected void dePost(HttpServletRequest request, HttpServletResponse response) throws ServletException, IOException {
    doGet(request, response);
}
```

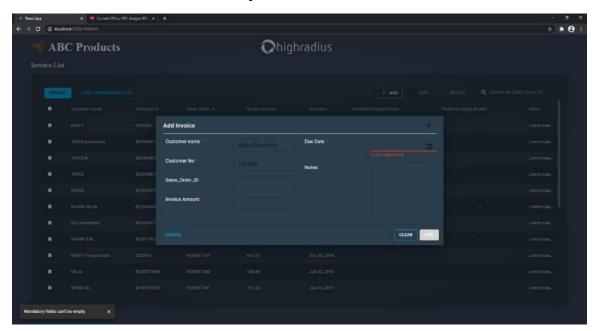
## 3.3.2.2.6 Invoice Fetch Servlet

## 3.3.3 Sales Order Management User Interface

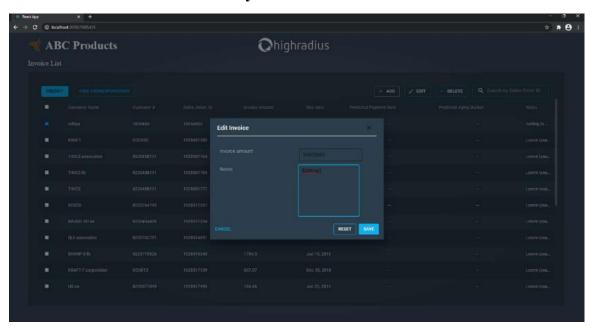
## 3.3.3.1 Landing Page Dashboard



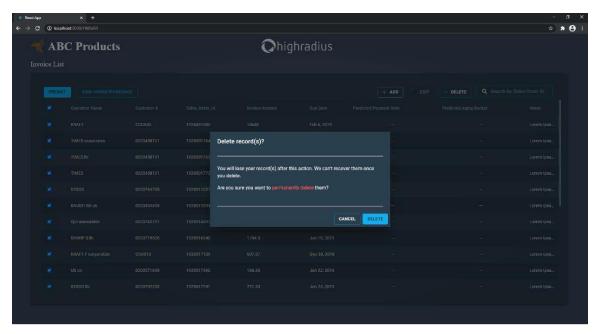
## 3.3.3.2 Add Invoice Functionality



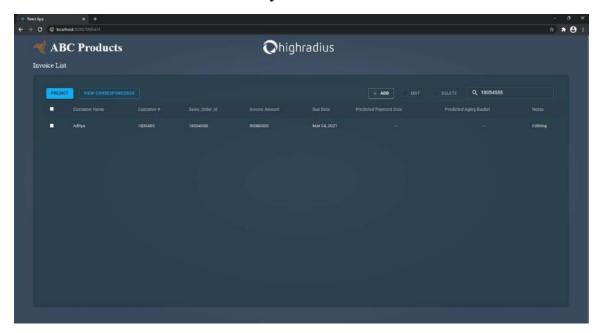
## 3.3.3.3 Edit Invoice Functionality



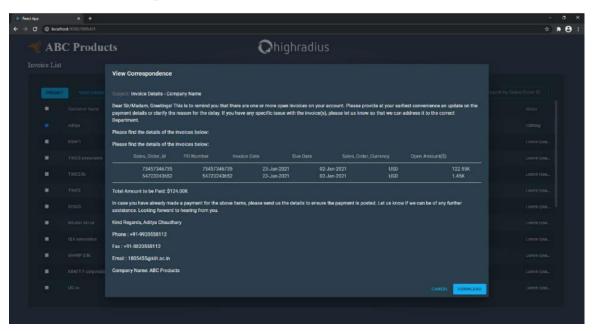
## **3.3.3.4 Delete Invoice Functionality**



## 3.3.3.5 Invoice Search Functionality



### 3.3.3.6 View Correspondence Functionality



#### 3.4 Research Methodology

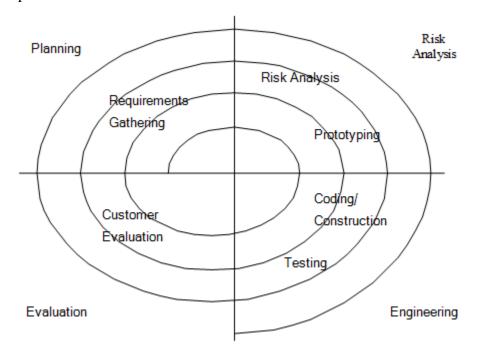
#### 3.4.1 Research Design

I will use the test type of the research design. It is a method of much research. Basically, it is a scientific study, in which a collection of variables are kept unchanged while other variables are measured as the subject matter. This is especially true when it comes to face recognition and acquisition as it takes into account the behavior and patterns of the topic that should be used to determine whether the topic complies with all the information presented and evaluated with previous information. It is a method of researching results as it is timely and focuses on the interactions between variables that give real results.

#### 3.4.2 System Development Methodology.

A software development method is a way to manage project development. There are many types of options available such as Waterfall model, Growing Model, RAD model, Agile model, design model and Spiral model. However, the engineer still needs to be consulted to determine what will be used in the project. The method model helps to manage the project efficiently and is able to assist the engineer in identifying any problem during development. Also, it helps to achieve the purpose and scope of projects. To build a project, it needs to understand the needs of the participants.

The methodology provides the framework for making the proposed DM model. This is a process that consists of steps that convert raw data into decent data patterns to extract information from users.



There are four phases that involve in the spiral model:

#### 1) Planning phase

The stage where collection and risk are required is assessed. This is the stage where the project title is discussed with the project manager. From that discussion, the Heart Guidance Program has been proposed. The need and risk were assessed after research into the existing system and a literature review was conducted with other available research.

#### 2) Risk analysis Phase

The stage where the risk is found and the other solution. An example is made at the end of this section. If there is a risk during this phase, there will be suggestions for another solution.

#### 3) Engineering phase

In this phase, software is developed and tests are performed at the end of this phase.

#### 4) Evaluation phase

At this stage, the user checks the software. This will be done after the system has been launched and the user will check if the system meets their expectations or needs or not. If there is an error, the user may report a problem with the system.

#### 3.5 Data Collection and Preprocessing.

The data set for this study were provided from the HRC database. The data had various anomalies like negative payments, which were cleaned up in the data preprocessing phase, few columns like the Currency column which had more than one type of currency were label encoded, similarly the business code column was hot encoded, and the customer payment terms and customer number columns were label encoded. Preprocessing and clearing of invalid date time was done in the data preprocessing phase.

#### **3.6 Tools**

Operating System	Windows 10 or any Linux Debian Distro.
Programming Languages	Python, JavaScript, JAVA, SQL.
Tools	Jupyter Notebook, Python , Microsoft Excel, VSCode, Eclipse IDE, SQLYog.
Technologies utilized	Machine Learning, Web Development.

## **3.7 Software Requirements**

Operating System	Any OS with client to use the internet	
Network	Wi-Fi Internet or Cellular Network	
Visual Studio Code	To run NPM commands	
Eclipse IDE	To run the Java Servlets	
SQLYog	To perform database actions	
Internet Browser	To run Jupyter Notebook and UI	

## 3.8 Hardware Requirements

For application development, the following Software Requirements are:

Processor: Intel i5-3570k or high equivalent

RAM: 8192 MB

Space on disk: minimum 6000MB

For running the application:

Device: Any device that can access the internet

Minimum space to execute: 1000MB

The effectiveness of the proposal is evaluated by conducting experiments on a system configured with an AMD Ryzen<sup>TM</sup> 5600x processor (4.37GHZ, 6 Cores, 32 GB RAM, running Windows 10 Home version 2004)

# CHAPTER 4 RESULTS & DISCUSSIONS

The proposed system is scalable, reliable and an expandable system. The proposed model gives an RMSE of 10.9 with the Random Forest Regression algorithm and RMSE of 9.5 with Multiple Linear Regression algorithm, but the Random Forest Algorithm performs better as the latter is greatly overfitting our training set, hence we proceed with the Random Forest Regression algorithm for predicting our unknown dates and get a good response.

# CHAPTER 5 CONCLUSION AND FUTURE WORK

#### 5.1 Conclusion & Future Work

The proposed application is easy to use, scalable, reliable and an expandable system. The proposed application can help in increasing the efficiency of Accounts Receivable Teams buy predicting the customer payment dates and bucketing them, and with this data the AR Team can take required steps to recover their credit from the customers thus increasing efficiency of the team and creating better cash flow for the company. This application also comes with integrated UI which allows, even people with no programming experience to use this software thus increasing the user base exponentially and increasing the applications accessibility. The backend is managed by Java and database is stored in a relational database which are industry standards for large scale applications and are known to be scalable and efficient.

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INDIVIDUAL CONTRIBUTION REPORT

SALES ORDER MANAGEMENT APPLICATION

ADITYA CHAUDHARY

1805455

Abstract: This Sales Order Management Application is implemented using Artificial

Intelligence to predict the payment dates, the backend and database of the application are

managed by Java JDBC, Java Servlets and SQLYog respectively. The application has an

User Interface which is programmed using HTML, CSS, JavaScript, React and Redux.

**Individual contribution and findings:** Planned the approach to finishing the project on

time, coded and developed everything from scratch for the project, learnt about various

new terminologies and technologies while working on this project, various websites and

reading materials were referenced for the completion of the project.

**Individual contribution to project report preparation:** I contributed to each and every

section of the project report preparation.

**Individual contribution for project presentation and demonstration:** I contributed to

each and every section of the presentation part.

Full Signature of Supervisor:

i dii 218iidda a 2 apai (18ai)

Sudakshina Chaudhury

Aditya Chaudhary
Full signature of the Student:

Aditya Chaudhary

## TURNITIN PLAGIARISM REPORT

# (This report is mandatory for all the projects and plagiarism must be below 30%)

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