# Project documentation

## Ecommerce Shipping Prediction with Machine Learning

# 1. Introduction

1.1. Project overviews

Machine Learning predicts specific e-commerce delivery dates, boosting sales and customer satisfaction.

1.2. Objectives

Develop a machine learning model for shipping predictions for ecommerce orders.

Historical order data, real-time carrier data, external data sources, predicting delivery ranges or specific delivery dates

# 2. Project Initialization and Planning Phase

### 2.1. Define Problem Statement

Ecommerce customers experience frustration due to inaccurate or unreliable shipping estimates, leading to a negative shopping experience.

### 2.2. Project Proposal (Proposed Solution)

Train machine learning models on historical data to predict future

e commerce delivery times.

### 2.3. Initial Project Planning

The plan outlines 3 phases:

1. Define & Understand: Identify business needs, gather relevant data, and explore it to understand factors affecting shipping times.
2. Model Development & Training: Engineer features from data, choose a suitable ML model, train it, and evaluate its performance.
3. Deployment & Monitoring: Deploy the model for use, monitor its performance, and retrain it periodically to maintain accuracy.

The plan emphasizes defining success criteria, acquiring resources, and establishing communication channels for a smooth project execution.

## 3.Data Collection and Preprocessing Phase

### 3.1. Data Collection Plan and Raw Data Sources Identified

This project uses data from a public source called Kaggle and this have 10000 records in it.

Now that we have the data, we'll explore it using different methods to get a better understanding. These methods include visualizations (like charts) and analysis techniques (like finding patterns). There are many other ways to explore data, but we'll focus on a few common ones here.

## Importing the libraries

Import the necessary libraries as shown in the image.

```
[1]: import numpy as np # linear algebra
     import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
     import seaborn as sns
     import matplotlib.pyplot as plt
     from sklearn.preprocessing import LabelEncoder , StandardScaler, MinMaxScaler
     from sklearn.model_selection import train_test_split, GridSearchCV
     from sklearn import svm
     from sklearn.ensemble import RandomForestClassifier
     from keras.models import Sequential
     from keras.layers import Dense
     from sklearn.linear_model import LogisticRegression
     from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
```

## 3.2. Data Quality Report

A Data Quality Report is basically a checkup for your data! It assesses how well your data meets your needs.

Here,Many data analysis tools, like pandas, can handle different file types you might encounter, including CSV, Excel, TXT, and JSON. In pandas, you can use the `read_csv()` function specifically for CSV files. Just point it to the location of your CSV file, and pandas will do the magic! It will take the data from that file and organize it into a neat table format called a DataFrame, making it much easier to work with and analyze.

Reading the dataset

```
[5]: dataset = pd.read_csv(r"C:\Users\harsha\OneDrive\Desktop\Train.csv")
     dataset.head()
```

[5]:

| | ID | Warehouse_block | Mode_of_Shipment | Customer_care_calls | Customer_rating | Cost_of_the_Product | Prior_purchases | Product_importance | Gender | Discount_offered |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 1 | D | Flight | 4 | 2 | 177 | 3 | low | F | 44 |
| 1 | 2 | F | Flight | 4 | 5 | 216 | 2 | low | M | 59 |
| 2 | 3 | A | Flight | 2 | 2 | 183 | 4 | low | M | 48 |
| 3 | 4 | B | Flight | 3 | 3 | 176 | 4 | medium | M | 10 |
| 4 | 5 | C | Flight | 2 | 2 | 184 | 3 | medium | F | 46 |

```
[7]: # Shape of the dataset
     dataset.shape
```

```
[7]: (10999, 12)
```

```
[9]: #Information about the columns
     dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10999 entries, 0 to 10998
Data columns (total 12 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   ID                   10999 non-null  int64
 1   Warehouse_block      10999 non-null  object
 2   Mode_of_Shipment     10999 non-null  object
 3   Customer_care_calls  10999 non-null  int64
 4   Customer_rating      10999 non-null  int64
 5   Cost_of_the_Product  10999 non-null  int64
 6   Prior_purchases      10999 non-null  int64
 7   Product_importance   10999 non-null  object
 8   Gender               10999 non-null  object
 9   Discount_offered     10999 non-null  int64
 10  Weight_in_gms        10999 non-null  int64
 11  Reached.on.Time_Y.N  10999 non-null  int64
dtypes: int64(8), object(4)
memory usage: 1.0+ MB
```

This gives us the information about the Dataset.

### 3.3. Data Exploration and Preprocessing

Our data might be messy right now, kind of like a dirty window. We can't see clearly through it, which is bad for machine learning models. So before we use the data, we need to clean it up. This cleaning process is called pre-processing. Here are some things we might do:

Handling missing values

Handling categorical data

Handling Outliers

## Handling missing values

Firstly we will check whether there are null values in the dataset and then handle those null values.

```
[11]: #Checking if there is any null values in the dataset
      dataset.isnull().sum()
```

```
[11]: ID                   0
      Warehouse_block      0
      Mode_of_Shipment     0
      Customer_care_calls  0
      Customer_rating      0
      Cost_of_the_Product  0
      Prior_purchases      0
      Product_importance   0
      Gender               0
      Discount_offered     0
      Weight_in_gms        0
      Reached.on.Time_Y.N  0
      dtype: int64
```

Since there are no null values in the dataset here there is no need of handling the null values.

### Data preprocessing

```
1]: #Dropping the ID column because of high cardinality
    data=dataset.drop(['ID'],axis=1)
    data.head()
```

1]:

| | Warehouse_block | Mode_of_Shipment | Customer_care_calls | Customer_rating | Cost_of_the_Product | Prior_purchases | Product_importance | Gender | Discount_offered | We |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | D | Flight | 4 | 2 | 177 | 3 | low | F | 44 | |
| 1 | F | Flight | 4 | 5 | 216 | 2 | low | M | 59 | |
| 2 | A | Flight | 2 | 2 | 183 | 4 | low | M | 48 | |
| 3 | B | Flight | 3 | 3 | 176 | 4 | medium | M | 10 | |
| 4 | C | Flight | 2 | 2 | 184 | 3 | medium | F | 46 | |

## Handling categorical data

```
[54]: #Dropping the ID column because of high cardinality
      data=dataset.drop(['ID'],axis=1)
      data.head()
```

[54]:

| | Warehouse_block | Mode_of_Shipment | Customer_care_calls | Customer_rating | Cost_of_the_Product | Prior_purchases | Product_importance | Gender | Discount_offered | W |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | D | Flight | 4 | 2 | 177 | 3 | low | F | 44 | |
| 1 | F | Flight | 4 | 5 | 216 | 2 | low | M | 59 | |
| 2 | A | Flight | 2 | 2 | 183 | 4 | low | M | 48 | |
| 3 | B | Flight | 3 | 3 | 176 | 4 | medium | M | 10 | |
| 4 | C | Flight | 2 | 2 | 184 | 3 | medium | F | 46 | |

### Chi square test of independence

[56]:
```
from sklearn.feature_selection import chi2
from scipy.stats import chi2_contingency
```

[58]:
```
#Warehouse_block
crossTab = pd.crosstab(data['Warehouse_block'], data['Reached.on.Time_Y.N'])
ChiSqResult = chi2_contingency(crossTab)
print("p-value ",ChiSqResult[1])
```

```
p-value  0.8959524278243698
```

[60]:
```
crossTab = pd.crosstab(data['Mode_of_Shipment'],data['Reached.on.Time_Y.N'])
ChiSqResult = chi2_contingency(crossTab)
print("p-value ",ChiSqResult[1])
```

```
p-value  0.6895487627593786
```

[62]:
```
# Product_importance
crossTab = pd.crosstab(data['Product_importance'],data['Reached.on.Time_Y.N'])
ChiSqResult = chi2_contingency(crossTab)
print("p-value ",ChiSqResult[1])
```

```
p-value  0.002230383104745087
```

[64]:
```
# Gender
crossTab = pd.crosstab(data['Gender'],data['Reached.on.Time_Y.N'])
ChiSqResult = chi2_contingency(crossTab)
print("p-value ",ChiSqResult[1])
```

```
p-value  0.6367032124181522
```

From chi square test, we can conclude that three of the independent categorical features are not related to the response variable

## Dropping unwanted columns

beacause the p value is greater than 0.05. So, these features can be removed and only product importance feature can be included

[66]:
```
#Renaming the column Reached.on.Time_Y.N
data.rename(columns={'Reached.on.Time_Y.N':'Reached on Time'}, inplace=True)
```

[68]:
```
X=data.drop(['Reached on Time','Warehouse_block','Mode_of_Shipment','Gender'],axis=1)
y=data['Reached on Time']
X
```

[68]:

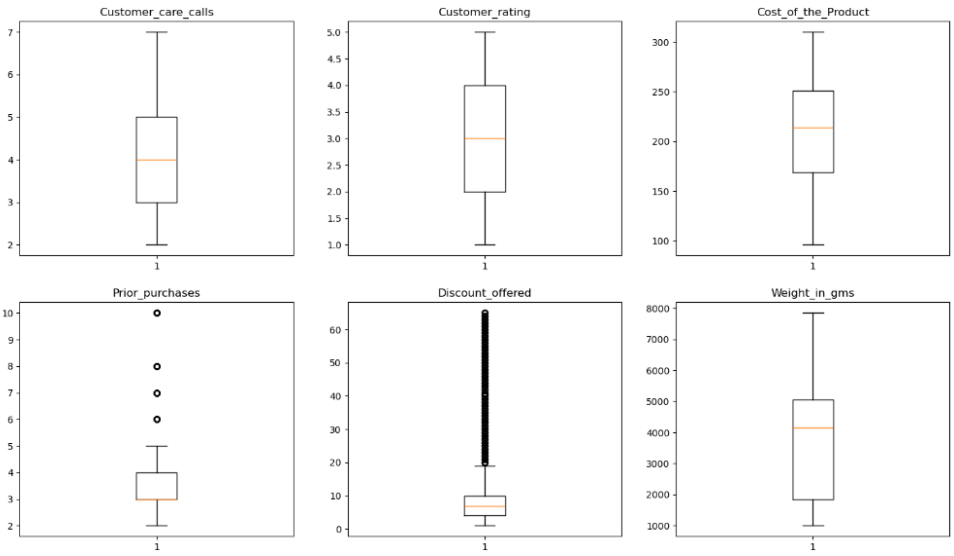
| | Customer_care_calls | Customer_rating | Cost_of_the_Product | Prior_purchases | Product_importance | Discount_offered | Weight_in_gms |
|---|---|---|---|---|---|---|---|
| **0** | 4 | 2 | 177 | 3 | low | 44 | 1233 |
| **1** | 4 | 5 | 216 | 2 | low | 59 | 3088 |
| **2** | 2 | 2 | 183 | 4 | low | 48 | 3374 |
| **3** | 3 | 3 | 176 | 4 | medium | 10 | 1177 |
| **4** | 2 | 2 | 184 | 3 | medium | 46 | 2484 |
| **...** | ... | ... | ... | ... | ... | ... | ... |
| **10994** | 4 | 1 | 252 | 5 | medium | 1 | 1538 |
| **10995** | 4 | 1 | 232 | 5 | medium | 6 | 1247 |
| **10996** | 5 | 4 | 242 | 5 | low | 4 | 1155 |
| **10997** | 5 | 2 | 223 | 6 | medium | 2 | 1210 |
| **10998** | 2 | 5 | 155 | 5 | low | 6 | 1639 |

10999 rows × 7 columns

# Handling Outliers

### Handling outliners

[48]:
```
C=0
plt.figure(figsize=(18, 10))
for i in dataset.drop(columns=[
    'Warehouse_block', 'Mode_of_Shipment', 'Gender', 'Reached.on.Time_Y.N', 'ID' ]).columns:
    if str(dataset[i].dtype)=='object':
        continue
    plt.subplot(2, 3, C+1)
    plt.boxplot(dataset[i])
    plt.title(i)
    C+=1
plt.show()
```



[50]:
```
def check_outliers(arr):
    Q1 = np.percentile(arr, 25, interpolation = 'midpoint')
    Q3 = np.percentile(arr, 75, interpolation = 'midpoint')
    IQR = Q3 - Q1

#Above Upper bound
    upper=Q3+1.5*IQR
    upper_array=np.array(arr>=upper)
    print(' '*3,len(upper_array[upper_array == True]), 'are over the upper bound:', upper)

    #BeLow Lower bound
    lower=Q1-1.5*IQR
    lower_array=np.array(arr<=lower)
    print(' '*3, len(lower_array[lower_array == True]), 'are less than the lower bound:', lower, '\n')

for i in dataset.drop(columns=[ 'Warehouse_block', 'Mode_of_Shipment', 'Gender', 'Reached.on.Time_Y.N', 'ID' ]).columns:
    if str(dataset[i].dtype)=='object':
        continue
    print(i)
    check_outliers(dataset[i])
```

```
Customer_care_calls
    0 are over the upper bound: 8.0
    0 are less than the lower bound: 0.0

Customer_rating
    0 are over the upper bound: 7.0
    0 are less than the lower bound: -1.0

Cost_of_the_Product
    0 are over the upper bound: 374.0
    0 are less than the lower bound: 46.0

Prior_purchases
    1003 are over the upper bound: 5.5
    0 are less than the lower bound: 1.5

Discount_offered
    2262 are over the upper bound: 19.0
    0 are less than the lower bound: -5.0

Weight_in_gms
    0 are over the upper bound: 9865.75
    0 are less than the lower bound: -2976.25
```

# 4.Model Development Phase

## 4.1. Feature Selection Report

A Feature Selection Report dives into the process of choosing the most informative and relevant features from your dataset for building a machine learning model. It's like picking the most important ingredients for a recipe – you wouldn't throw everything in the kitchen sink, right?  So here we remove the unwanted columns and keep the required columns only in the dataset and encode the Alphabetical values to the numeric values. Using the Encoders  we can process the data into the required form.

[63]:
```
#Renaming the column Reached.on.Time_Y.N
data.rename(columns={'Reached.on.Time_Y.N':'Reached on Time'}, inplace=True)
```

[65]:
```
X=data.drop(['Reached on Time','Warehouse_block','Mode_of_Shipment','Gender'],axis=1)
y=data['Reached on Time']
X.head()
```

[65]:

| | Customer_care_calls | Customer_rating | Cost_of_the_Product | Prior_purchases | Product_importance | Discount_offered | Weight_in_gms |
|---|---|---|---|---|---|---|---|
| **0** | 4 | 2 | 177 | 3 | low | 44 | 1233 |
| **1** | 4 | 5 | 216 | 2 | low | 59 | 3088 |
| **2** | 2 | 2 | 183 | 4 | low | 48 | 3374 |
| **3** | 3 | 3 | 176 | 4 | medium | 10 | 1177 |
| **4** | 2 | 2 | 184 | 3 | medium | 46 | 2484 |

[78]:
```
from sklearn.preprocessing import LabelEncoder
```

[80]:
```
le=LabelEncoder()
```

[82]:
```
y = le.fit_transform(y)
```

[84]:
```
y
```

[84]:
```
array([1, 1, 1, ..., 0, 0, 0])
```

[86]:
```
X_train, X_test, y_train, y_test = train_test_split(x,y,test_size=0.3, random_state=42)

#Scaling the data
ms = MinMaxScaler()
X_train = ms.fit_transform(X_train)
X_test = ms.fit_transform(X_test)
```

Let us see the total discrimination about the data that we have preprocessed.

[13]:
```
#Basic summary statistics
dataset.describe()
```

[13]:

| | ID | Customer_care_calls | Customer_rating | Cost_of_the_Product | Prior_purchases | Discount_offered | Weight_in_gms | Reached.on.Time_Y.N |
|---|---|---|---|---|---|---|---|---|
| **count** | 10999.00000 | 10999.000000 | 10999.000000 | 10999.000000 | 10999.000000 | 10999.000000 | 10999.000000 | 10999.000000 |
| **mean** | 5500.00000 | 4.054459 | 2.990545 | 210.196836 | 3.567597 | 13.373216 | 3634.016729 | 0.596691 |
| **std** | 3175.28214 | 1.141490 | 1.413603 | 48.063272 | 1.522860 | 16.205527 | 1635.377251 | 0.490584 |
| **min** | 1.00000 | 2.000000 | 1.000000 | 96.000000 | 2.000000 | 1.000000 | 1001.000000 | 0.000000 |
| **25%** | 2750.50000 | 3.000000 | 2.000000 | 169.000000 | 3.000000 | 4.000000 | 1839.500000 | 0.000000 |
| **50%** | 5500.00000 | 4.000000 | 3.000000 | 214.000000 | 3.000000 | 7.000000 | 4149.000000 | 1.000000 |
| **75%** | 8249.50000 | 5.000000 | 4.000000 | 251.000000 | 4.000000 | 10.000000 | 5050.000000 | 1.000000 |
| **max** | 10999.00000 | 7.000000 | 5.000000 | 310.000000 | 10.000000 | 65.000000 | 7846.000000 | 1.000000 |

## Exploratory Data Analysis

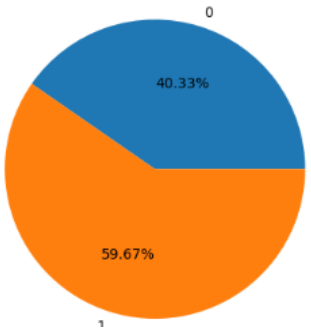
[15]:
```
dataset.head()
```

[15]:

| | ID | Warehouse_block | Mode_of_Shipment | Customer_care_calls | Customer_rating | Cost_of_the_Product | Prior_purchases | Product_importance | Gender | Discount_offered |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 1 | D | Flight | 4 | 2 | 177 | 3 | low | F | 44 |
| 1 | 2 | F | Flight | 4 | 5 | 216 | 2 | low | M | 59 |
| 2 | 3 | A | Flight | 2 | 2 | 183 | 4 | low | M | 48 |
| 3 | 4 | B | Flight | 3 | 3 | 176 | 4 | medium | M | 10 |
| 4 | 5 | C | Flight | 2 | 2 | 184 | 3 | medium | F | 46 |

[17]:
```
delay=pd.DataFrame(dataset.groupby(['Reached.on.Time_Y.N'])['ID'].count()/len(dataset)).reset_index()
plt.pie(delay['ID'],labels=delay['Reached.on.Time_Y.N'],autopct='%1.2f%%')
```

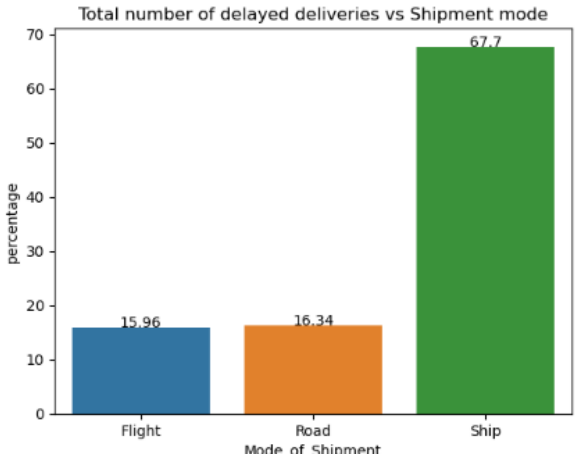
[17]:
```
([<matplotlib.patches.Wedge at 0x21cf0389f50>,
  <matplotlib.patches.Wedge at 0x21cf03e8650>],
 [Text(0.32902377754583456, 1.0496396304491695, '0'),
  Text(-0.32902377754583423, -1.0496396304491697, '1')],
 [Text(0.17946751502500063, 0.5725307075177288, '40.33%'),
  Text(-0.17946751502500047, -0.5725307075177288, '59.67%')])
```




[19]:
```
data_v1 = dataset[dataset['Reached.on.Time_Y.N']==0]
```

[21]:
```
data_v2=pd.DataFrame((data_v1.groupby(['Mode_of_Shipment'])['ID'].count())/len(data_v1)*100)
data_v2=data_v2.reset_index()
visual=sns.barplot(x="Mode_of_Shipment", y="ID", data=data_v2 )
for index, row in data_v2.iterrows():
    visual.text(row.name,row.ID, round(row.ID,2), color='black', ha="center")
plt.title('Total number of delayed deliveries vs Shipment mode')
plt.ylabel('percentage')
```

[21]:
```
Text(0, 0.5, 'percentage')
```

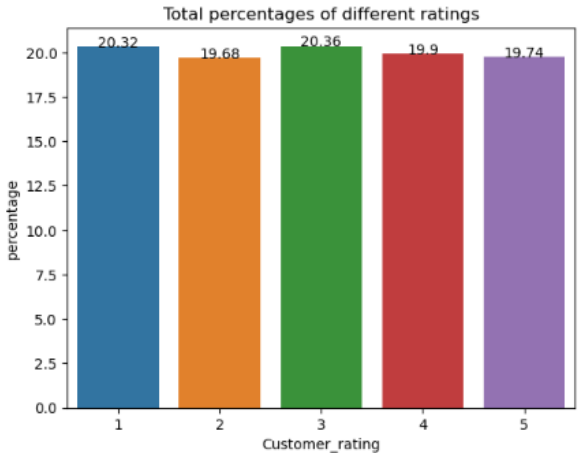


[23]:
```
data_v3=pd.DataFrame((data_v1.groupby(['Warehouse_block'])['ID'].count())/len(data_v1)*100)
data_v3=data_v3.reset_index()
visual=sns.barplot(x="Warehouse_block", y="ID", data=data_v3 )
for index, row in data_v3.iterrows():
    visual.text(row.name,row.ID, round(row.ID,2), color='black', ha="center")
plt.title('Total number of delayed deliveries vs Warehouse block')
plt.ylabel('percentage')
```

[23]:
```
Text(0, 0.5, 'percentage')
```


[25]:
```
data_v4=pd.DataFrame((dataset.groupby(['Customer_rating'])['ID'].count())/len(dataset)*100)
data_v4=data_v4.reset_index()
visual=sns.barplot(x="Customer_rating", y="ID", data=data_v4 )
for index, row in data_v4.iterrows():
    visual.text(row.name,row.ID, round(row.ID,2), color='black', ha="center")
plt.title('Total percentages of different ratings')
plt.ylabel('percentage')
```

[25]:
```
Text(0, 0.5, 'percentage')
```



[27]:
```
dataset['Reached.on.Time_Y.N'].replace({1 : "Yes", 0: "No"}, inplace = True)
```

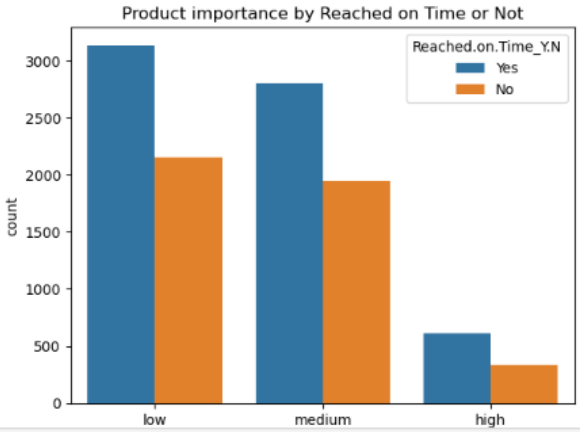
[29]:
```
dataset.head()
```

[29]:

| | ID | Warehouse_block | Mode_of_Shipment | Customer_care_calls | Customer_rating | Cost_of_the_Product | Prior_purchases | Product_importance | Gender | Discount_offered |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | D | Flight | 4 | 2 | 177 | 3 | low | F | 44 |
| **1** | 2 | F | Flight | 4 | 5 | 216 | 2 | low | M | 59 |
| **2** | 3 | A | Flight | 2 | 2 | 183 | 4 | low | M | 48 |
| **3** | 4 | B | Flight | 3 | 3 | 176 | 4 | medium | M | 10 |
| **4** | 5 | C | Flight | 2 | 2 | 184 | 3 | medium | F | 46 |

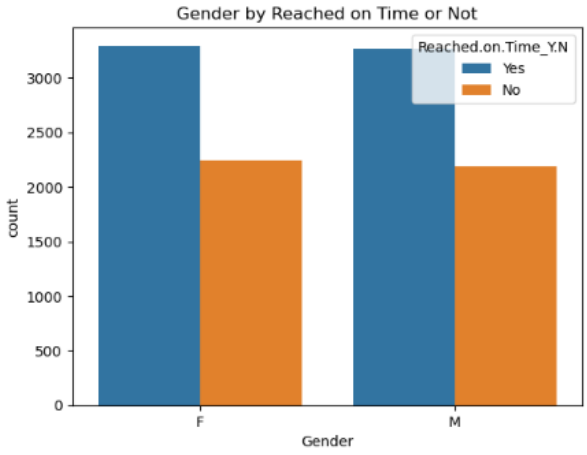
[31]:
```
sns.countplot(x = "Product_importance", data = dataset, hue="Reached.on.Time_Y.N")
plt.title("Product importance by Reached on Time or Not")
```

[31]:
```
Text(0.5, 1.0, 'Product importance by Reached on Time or Not')
```



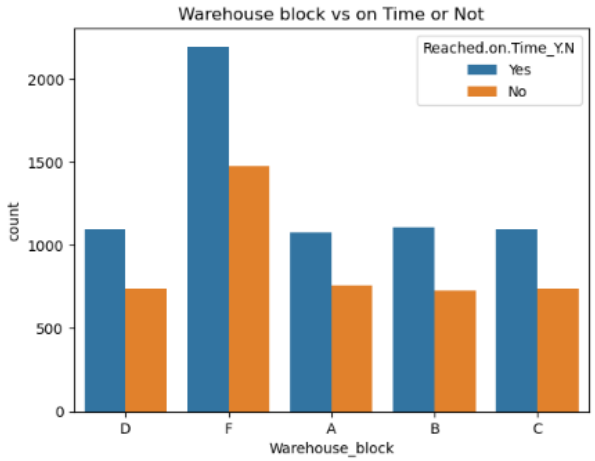

[33]:
```
sns.countplot(x = "Gender", data = dataset, hue="Reached.on.Time_Y.N")
plt.title("Gender by Reached on Time or Not")
```

[33]:
```
Text(0.5, 1.0, 'Gender by Reached on Time or Not')
```



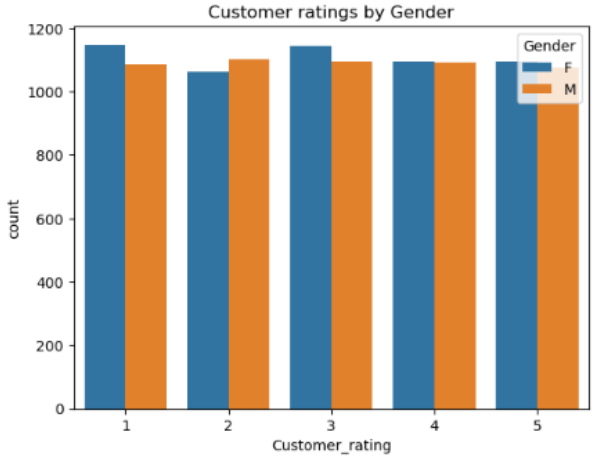
[35]:
```
sns.countplot(x = "Warehouse_block", data = dataset, hue = 'Reached.on.Time_Y.N' )
plt.title("Warehouse block vs on Time or Not")
```

[35]: Text(0.5, 1.0, 'Warehouse block vs on Time or Not')



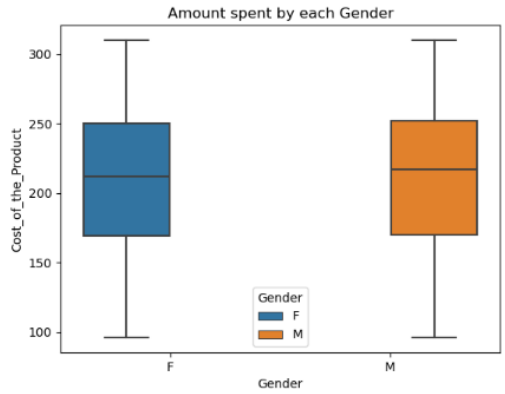

[37]:
```
sns.countplot(x = "Customer_rating", data = dataset, hue="Gender")
plt.title("Customer ratings by Gender")
```

[37]: Text(0.5, 1.0, 'Customer ratings by Gender')



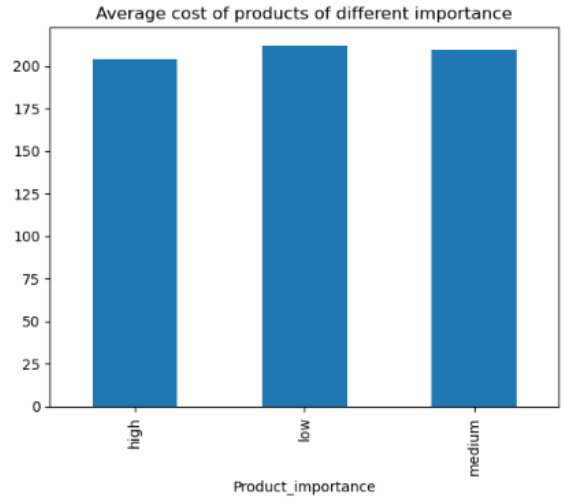

[39]:
```
sns.boxplot(x='Gender',y='Cost_of_the_Product',data=dataset,hue='Gender')
plt.title("Amount spent by each Gender")
```

[39]: Text(0.5, 1.0, 'Amount spent by each Gender')



[41]:
```
dataset.groupby(['Product_importance'])['Cost_of_the_Product'].mean().plot.bar()
plt.title("Average cost of products of different importance")
```

[41]:
```
Text(0.5, 1.0, 'Average cost of products of different importance')
```



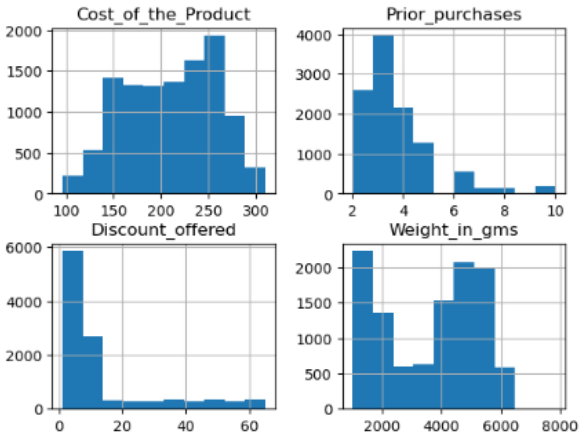

[43]:
```
dataset.head()
```

[43]:

| | ID | Warehouse_block | Mode_of_Shipment | Customer_care_calls | Customer_rating | Cost_of_the_Product | Prior_purchases | Product_importance | Gender | Discount_offered |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | D | Flight | 4 | 2 | 177 | 3 | low | F | 44 |
| **1** | 2 | F | Flight | 4 | 5 | 216 | 2 | low | M | 59 |
| **2** | 3 | A | Flight | 2 | 2 | 183 | 4 | low | M | 48 |
| **3** | 4 | B | Flight | 3 | 3 | 176 | 4 | medium | M | 10 |
| **4** | 5 | C | Flight | 2 | 2 | 184 | 3 | medium | F | 46 |

[45]:
```
dataset[['Cost_of_the_Product','Prior_purchases','Discount_offered','Weight_in_gms']].hist()
```

[45]:
```
array([[<Axes: title={'center': 'Cost_of_the_Product'}>,
        <Axes: title={'center': 'Prior_purchases'}>],
       [<Axes: title={'center': 'Discount_offered'}>,
        <Axes: title={'center': 'Weight_in_gms'}>]], dtype=object)
```



```
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.3, random_state=42)

#Scaling the data
ms = MinMaxScaler()
X_train = ms.fit_transform(X_train)
X_test = ms.fit_transform(X_test)
```

The process that is done here is,

## Splitting the Data: Preparing for Learning and Assessment

The preprocessed data serves as the fuel for our model. However, we don't simply throw it all at the model at once. A strategic data split is crucial:

**Training Set :**This serves as the basis for the learning process of the model. The features (such as order weight, distance) and their correlation with the goal variable (such as on-time vs. late delivery, expected delivery time) are presented to the model. The model gains the ability to recognize links and patterns via this exposure, which will help it forecast data that has not yet been observed.

**Testing Set :** The last test for the generalizability of the model is conducted on this untested set. Select metrics are used to evaluate the model on the testing set after it has been trained on the training data and maybe fine-tuned using the validation set. This gives an objective evaluation of the model's performance on data that it has never seen before.

Crucially important is the size of each split (training, validation, and testing). Typically, 60–80% of the data are set aside for training, 10–20% for validation, and 10–20% for testing. Depending on the size and features of the dataset, the precise allocation can be changed.

### 4.2. Model Selection Report

A Model Selection Report acts like a guide for choosing the **champion** among machine learning models for your project. Imagine you're training a bunch of athletes (models) for a competition (solving a specific task). The Model Selection Report helps pick the one who will perform the best. Here There are many models that we used like,

Support Vector Classifier
Logistic Regression
Decision Tree classifier
KNN
Naive Bayes
XGBoost
Ada Boost
Gradient Boosting,
Decision Tree classifer
Artificial Neural Network

Here are the particular codes for the models that are trained.

## 1. Support Vector Classifier

[88]:
```
svm_model = svm.SVC(gamma='auto',C=5,kernel='rbf')
svm_model.fit(X_train,y_train)
y_pred = svm_model.predict(X_test)
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.54      0.85      0.66      1312
           1       0.84      0.53      0.65      1988

    accuracy                           0.66      3300
   macro avg       0.69      0.69      0.66      3300
weighted avg       0.72      0.66      0.65      3300
```

[90]:
```
print(confusion_matrix(y_test,y_pred))
```

```
[[1119  193]
 [ 940 1048]]
```

## 2. Logistic Regression

[92]:
```
from sklearn.linear_model import LogisticRegression
```

[94]:
```
lr=LogisticRegression()
lr.fit(X_train,y_train)
predLR=lr.predict(X_test)
print(classification_report(y_test,predLR))
```

```
              precision    recall  f1-score   support

           0       0.54      0.59      0.56      1312
           1       0.71      0.67      0.69      1988

    accuracy                           0.64      3300
   macro avg       0.63      0.63      0.63      3300
weighted avg       0.64      0.64      0.64      3300
```

[96]:
```
print(confusion_matrix(y_test,predLR))
```

```
[[ 771  541]
 [ 651 1337]]
```

## 3. Decision Tree classifier

[98]:
```
from sklearn.tree import DecisionTreeClassifier
```

[100]:
```
df=DecisionTreeClassifier(criterion='entropy',random_state=0)
df.fit(X_train,y_train)
preddf=df.predict(X_test)
print(classification_report(y_test,preddf))
```

```
              precision    recall  f1-score   support

           0       0.56      0.59      0.58      1312
           1       0.72      0.70      0.71      1988

    accuracy                           0.66      3300
   macro avg       0.64      0.64      0.64      3300
weighted avg       0.66      0.66      0.66      3300
```

[102]:
```
print(confusion_matrix(y_test,preddf))
```

```
[[ 769  543]
 [ 593 1395]]
```

# 4. KNN

```
from sklearn.neighbors import KNeighborsClassifier
```

```
knn=KNeighborsClassifier()
knn.fit(X_train,y_train)
predknn=knn.predict(X_test)
print(classification_report(y_test,predknn))
```

```
              precision    recall  f1-score   support

           0       0.55      0.61      0.58      1312
           1       0.72      0.67      0.70      1988

    accuracy                           0.65      3300
   macro avg       0.64      0.64      0.64      3300
weighted avg       0.65      0.65      0.65      3300
```

```
print(confusion_matrix(y_test,predknn))
```

```
[[ 802  510]
 [ 655 1333]]
```

# 5. Naive Bayes

[110]:
```
from sklearn.naive_bayes import GaussianNB
nb = GaussianNB()
```

[112]:
```
nb.fit(X_train,y_train)
prednb = nb.predict(X_test)
print(classification_report(prednb,y_test))
```

```
              precision    recall  f1-score   support

           0       0.98      0.53      0.69      2415
           1       0.43      0.97      0.60       885

    accuracy                           0.65      3300
   macro avg       0.70      0.75      0.64      3300
weighted avg       0.83      0.65      0.66      3300
```

[114]:
```
print(confusion_matrix(prednb,y_test))
```

```
[[1283 1132]
 [  29  856]]
```

# 6.XGBoost

[118]:
```
import xgboost as xgb
xg=xgb.XGBClassifier()
xg.fit(X_train,y_train)
predxg = xg.predict(X_test)
print(classification_report(prednb,y_test))
```

```
              precision    recall  f1-score   support

           0       0.98      0.53      0.69      2415
           1       0.43      0.97      0.60       885

    accuracy                           0.65      3300
   macro avg       0.70      0.75      0.64      3300
weighted avg       0.83      0.65      0.66      3300
```

[120]:
```
print(confusion_matrix(prednb,y_test))
```

```
[[1283 1132]
 [  29  856]]
```

# 7. Ada Boost and Gradient Boosting,

[122]:
```
from sklearn.ensemble import AdaBoostClassifier, GradientBoostingClassifier
```

[124]:
```
ab=AdaBoostClassifier()
gb=GradientBoostingClassifier()
```

[126]:
```
ab.fit(X_train,y_train)
```

```
C:\Users\harsha\anaconda3\Lib\site-packages\sklearn\ensemble\_weight_boosting.py:527: FutureWarning: The SAMME.R algorithm (the def
ault) is deprecated and will be removed in 1.6. Use the SAMME algorithm to circumvent this warning.
  warnings.warn(
```

[126]:
```
AdaBoostClassifier()
```

[128]:
```
gb.fit(X_train,y_train)
```

[128]:
```
GradientBoostingClassifier()
```

[130]:
```
pred2= ab.predict(X_test)
pred3= gb.predict(X_test)
```

[132]:
```
print(classification_report(y_test, pred2))
```

```
              precision    recall  f1-score   support

           0       0.57      0.76      0.65      1312
           1       0.79      0.62      0.69      1988

    accuracy                           0.67      3300
   macro avg       0.68      0.69      0.67      3300
weighted avg       0.70      0.67      0.68      3300
```

[134]:
```
print(confusion_matrix(y_test, pred2))
```

```
[[ 995  317]
 [ 765 1223]]
```

[136]:
```
print(classification_report(y_test, pred3))
```

```
              precision    recall  f1-score   support

           0       0.56      0.87      0.68      1312
           1       0.87      0.55      0.67      1988

    accuracy                           0.68      3300
   macro avg       0.71      0.71      0.68      3300
weighted avg       0.75      0.68      0.68      3300
```

[138]:
```
print(confusion_matrix(y_test, pred3))
```

```
[[1142  170]
 [ 889 1099]]
```

# 4.3. Initial Model Training Code, Model Validation and Evaluation Report.

### Evaluation before Tuning

[140]:
```
from sklearn.metrics import accuracy_score, f1_score, recall_score, precision_score

def eval(name, model):
    y_pred = model.predict(X_test)
    result = []
    result.append(name)
    result.append("{:.2f}".format(accuracy_score(y_test, y_pred) * 100))
    result.append("{:.2f}".format(f1_score(y_test, y_pred) * 100))
    result.append("{:.2f}".format(recall_score(y_test, y_pred) * 100))
    result.append("{:.2f}".format(precision_score(y_test, y_pred) * 100))
    return result
```

[142]:
```
model_list = {
    'Logistic Regression':lr,
    'XGBoost':xg,
    'Ada Boost':ab,
    'Gradient Boosting' : gb,
    'Support Vector Classifier': svm_model,
    'Naive Bias' : nb,
    'KNN' : knn,
    'Decision Tree' : df,

}


model_eval_info = []
for i in model_list.keys():
    model_eval_info.append(eval(i,model_list[i]))
model_eval_info = pd.DataFrame(model_eval_info, columns=['Name', 'Accuracy', 'fl_score', 'Recall', 'Precision'])
model_eval_info.to_csv('model_eval.csv')
model_eval_info
```

# Evaluation report:

[142]:

| | Name | Accuracy | fl_score | Recall | Precision |
|---|---|---|---|---|---|
| **0** | Logistic Regression | 63.88 | 69.17 | 67.25 | 71.19 |
| **1** | XGBoost | 66.76 | 70.75 | 66.75 | 75.27 |
| **2** | Ada Boost | 67.21 | 69.33 | 61.52 | 79.42 |
| **3** | Gradient Boosting | 67.91 | 67.49 | 55.28 | 86.60 |
| **4** | Support Vector Classifier | 65.67 | 64.91 | 52.72 | 84.45 |
| **5** | Naive Bias | 64.82 | 59.59 | 43.06 | 96.72 |
| **6** | KNN | 64.70 | 69.59 | 67.05 | 72.33 |
| **7** | Decision Tree | 65.58 | 71.06 | 70.17 | 71.98 |

# 5.Model Optimization and Tuning Phase

## 5.1. Hyperparameter Tuning Documentation

Hyperparameter tuning is a critical step in the machine learning workflow that involves adjusting the settings of your model to achieve the best possible performance. It's like fine-tuning the dials on a radio to get the clearest signal. In this documentation, we'll delve into the world of hyperparameter tuning, explaining its importance, common techniques, and best practices.

## Random Forest Classifier

**Hyperparametric Tuning**

[144]:
```
params = {'n_estimators':[150,500], 'criterion':['gini', 'entropy'], 'max_depth' : [7],
          'max_features' : [60,80,100]
         }
#Hyper parameter tuning
rf_model =GridSearchCV(estimator=RandomForestClassifier(),param_grid=params,scoring='accuracy', n_jobs = -1, cv=7, verbose = 3)
rf_model.fit(X_train,y_train)
y_pred=rf_model.predict(X_test)
print(classification_report(y_test,y_pred))
```

```
Fitting 7 folds for each of 12 candidates, totalling 84 fits
              precision    recall  f1-score   support

           0       0.56      0.93      0.70      1312
           1       0.92      0.52      0.67      1988

    accuracy                           0.68      3300
   macro avg       0.74      0.73      0.68      3300
weighted avg       0.78      0.68      0.68      3300
```

[146]:
```
print(confusion_matrix(y_test,y_pred))
```

```
[[1224   88]
 [ 953 1035]]
```

---

## XG Boost Classifier

[148]:
```
params2 = {'min_child_weight' : [10,20],
          'gamma' : [1.5,2.0,2.5],
          'colsample_bytree' : [0.6,0.8,0.9],
          'max_depth' : [4,5,6]
          }
xgb1 = xgb.XGBClassifier(learning_rate=0.5, n_estimators = 100 , objective = 'binary:logistic', nthread=3)
fitmodelXGB = GridSearchCV(xgb1,param_grid = params2, cv=5, refit = True , scoring = "accuracy", n_jobs = -1, verbose = 3)
fitmodelXGB.fit(X_train,y_train)
y_pred1=fitmodelXGB.predict(X_test)
print(classification_report(y_test,y_pred1))
```

```
Fitting 5 folds for each of 54 candidates, totalling 270 fits
              precision    recall  f1-score   support

           0       0.56      0.85      0.68      1312
           1       0.85      0.56      0.68      1988

    accuracy                           0.68      3300
   macro avg       0.71      0.71      0.68      3300
weighted avg       0.73      0.68      0.68      3300
```

[150]:
```
print(confusion_matrix(y_test,y_pred1))
```

```
[[1113  199]
 [ 868 1120]]
```

# Logistic Regression

[152]:
```
lg = LogisticRegression(n_jobs= -1 , random_state = 2)
params3 = {
    'C' : [6,8,10,15,20],
    'max_iter' : [60,80,100]
}
fitmodelLR = GridSearchCV(lg,param_grid = params3, cv=5, refit = True , scoring = "accuracy", n_jobs = -1, verbose = 3)
fitmodelLR.fit(X_train,y_train)
y_pred2=fitmodelLR.predict(X_test)
print(classification_report(y_test,y_pred2))

print("Best Score:")
print(fitmodelXGB.best_score_)
```

```
Fitting 5 folds for each of 15 candidates, totalling 75 fits
              precision    recall  f1-score   support

           0       0.54      0.59      0.56      1312
           1       0.71      0.67      0.69      1988

    accuracy                           0.64      3300
   macro avg       0.63      0.63      0.63      3300
weighted avg       0.64      0.64      0.64      3300

Best Score:
0.6824271115499185
```

[154]:
```
print(confusion_matrix(y_test,y_pred2))
```

```
[[ 774  538]
 [ 658 1330]]
```

# Support Vector Machine

```
svc = svm.SVC(random_state =3)
params4 = {
    'kernel' : ['ploy','rbf'],
    'C' : [10,13],
    'gamma' : [4,5],
    'tol' : [1e-1,1e-2,1e-3]
}
fitmodelSVC = GridSearchCV(svc,param_grid = params4, cv=5, refit = True , scoring = "accuracy", n_jobs = -1, verbose = 3)
fitmodelSVC.fit(X_train,y_train)
y_pred3=fitmodelLR.predict(X_test)
print(classification_report(y_test,y_pred3))
```

# Artificial Neural Network

[156]:
```
ann = Sequential()
```

[158]:
```
ann.add(Dense(14,activation='relu'))
ann.add(Dense(26,activation='relu'))
ann.add(Dense(26,activation='relu'))
ann.add(Dense(1,activation='sigmoid'))
ann.compile(loss="binary_crossentropy", optimizer='adam',metrics=['accuracy'])
```

[160]:
```
ann.fit(X_train, y_train, epochs=50, batch_size=15)
```

```
Epoch 1/50
514/514 ━━━━━━━━━━━━━━━━━━━━ 3s 805us/step - accuracy: 0.6064 - loss: 0.6383
Epoch 2/50
514/514 ━━━━━━━━━━━━━━━━━━━━ 1s 921us/step - accuracy: 0.6379 - loss: 0.5391
Epoch 3/50
514/514 ━━━━━━━━━━━━━━━━━━━━ 0s 811us/step - accuracy: 0.6599 - loss: 0.5256
Epoch 4/50
514/514 ━━━━━━━━━━━━━━━━━━━━ 0s 835us/step - accuracy: 0.6600 - loss: 0.5283
Epoch 5/50
514/514 ━━━━━━━━━━━━━━━━━━━━ 0s 902us/step - accuracy: 0.6663 - loss: 0.5259
Epoch 6/50
514/514 ━━━━━━━━━━━━━━━━━━━━ 0s 831us/step - accuracy: 0.6569 - loss: 0.5228
Epoch 7/50
514/514 ━━━━━━━━━━━━━━━━━━━━ 0s 837us/step - accuracy: 0.6687 - loss: 0.5204
Epoch 8/50
514/514 ━━━━━━━━━━━━━━━━━━━━ 0s 860us/step - accuracy: 0.6658 - loss: 0.5210
```

```
[162]: predictions = (ann.predict(X_test) > 0.5)
       print(classification_report(y_test,predictions))
```

```
104/104 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
              precision    recall  f1-score   support

           0       0.55      0.85      0.67      1312
           1       0.85      0.54      0.66      1988

    accuracy                           0.66      3300
   macro avg       0.70      0.70      0.66      3300
weighted avg       0.73      0.66      0.66      3300
```

```
[164]: print(confusion_matrix(y_test,predictions))
```

```
[[1120  192]
 [ 915 1073]]
```

# 5.2. Performance Metrics Comparison Report

A performance metrics comparison report evaluates a business's performance against benchmarks, competitors, or internal targets. It uses key performance indicators (KPIs) to analyze trends, identify strengths and weaknesses, and suggest improvements.

```
def hyper_eval(name, model):
    y_pred_prob = model.predict(X_test)

    if y_pred_prob.ndim == 2 and y_pred_prob.shape[1] > 1:
        y_pred = y_pred_prob.argmax(axis=1)
    else:
        y_pred = (y_pred_prob >= 0.5).astype(int)  # For binary

    result = []
    result.append(name)
    result.append("{:.2f}".format(accuracy_score(y_test, y_pred) * 100))
    result.append("{:.2f}".format(f1_score(y_test, y_pred, average='weighted') * 100))
    result.append("{:.2f}".format(recall_score(y_test, y_pred, average='weighted') * 100))
    result.append("{:.2f}".format(precision_score(y_test, y_pred, average='weighted') * 100))
    return result

# Example usage:
model_list = {
    'Logistic Regression(Hyper)': fitmodelLR,
    'XGBoost(Hyper)': fitmodelXGB,
    'Random Forest(Hyper)': rf_model,
    'ANN': ann,
    'SVC' : fitmodelSVC
}

model_hyper_eval_info = []
for name, model in model_list.items():
    model_hyper_eval_info.append(hyper_eval(name, model))

model_hyper_eval_info = pd.DataFrame(model_hyper_eval_info, columns=['Name', 'Accuracy', 'F1_Score', 'Recall', 'Precision'])
model_hyper_eval_info.to_csv('model_hyper_eval.csv', index=False)
model_hyper_eval_info
```

| | Name | Accuracy | F1_Score | Recall | Precision |
|---|---|---|---|---|---|
| 0 | Logistic Regression(Hyper) | 63.97 | 64.19 | 63.97 | 64.57 |
| 1 | XGBoost(Hyper) | 68.24 | 67.98 | 68.24 | 76.09 |
| 2 | Random Forest(Hyper) | 68.52 | 68.06 | 68.52 | 77.82 |
| 3 | ANN | 65.94 | 66.30 | 65.94 | 67.89 |
| 4 | SVC | 66.85 | 67.11 | 66.85 | 70.53 |

## 5.3. Final Model Selection Justification

| | Name | Accuracy | fl_score | Recall | Precision |
|---|---|---|---|---|---|
| 0 | Logistic Regression | 63.79 | 69.15 | 67.35 | 71.03 |
| 1 | XGBoost | 66.76 | 70.89 | 67.20 | 75.01 |
| 2 | Ada Boost | 67.21 | 69.33 | 61.52 | 79.42 |
| 3 | Gradient Boosting | 68.39 | 68.21 | 56.29 | 86.54 |
| 4 | Support Vector Classifier | 66.27 | 64.52 | 50.91 | 88.08 |
| 5 | Naive Bias | 64.73 | 59.04 | 42.20 | 98.24 |
| 6 | KNN | 64.70 | 69.59 | 67.05 | 72.33 |
| 7 | Decision Tree | 65.52 | 70.92 | 69.82 | 72.07 |

| | Name | Accuracy | F1_Score | Recall | Precision |
|---|---|---|---|---|---|
| 0 | Logistic Regression(Hyper) | 63.97 | 64.19 | 63.97 | 64.57 |
| 1 | XGBoost(Hyper) | 68.24 | 67.98 | 68.24 | 76.09 |
| 2 | Random Forest(Hyper) | 68.52 | 68.06 | 68.52 | 77.82 |
| 3 | ANN | 65.94 | 66.30 | 65.94 | 67.89 |
| 4 | SVC | 66.85 | 67.11 | 66.85 | 70.53 |

**The Random Forest model is chosen as the best model due to its superior performance and efficiency.**

**High accuracy:** It consistently outperforms other models in predicting outcomes.

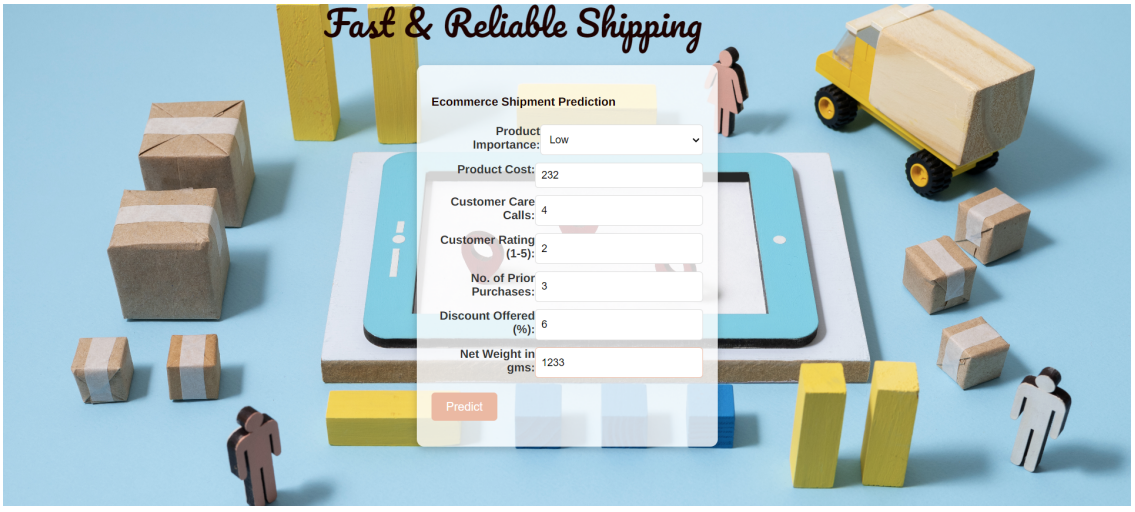
**Efficiency:** It handles large datasets effectively and requires reasonable computational resources.

Compared to other models, Random Forest demonstrated advantages in terms of accuracy and robustness. Hyperparameter tuning, feature engineering, and rigorous validation were employed to optimize the model's performance.

Overall, Random Forest is deemed reliable for accurate predictions and informed decision-making.

# 6.Results

## Output Screenshots




# 7. Advantages & Disadvantages

## Advantages :

• **Better Customer Experience**: Precise shipping estimates help clients set reasonable expectations, which lowers annoyance and boosts confidence in your company.

• **Increased Operational Efficiency:** You may more effectively deploy resources for fulfillment and delivery by forecasting shipment timeframes, which can result in more seamless operations and possibly cheaper costs.

• **Lower Shipping Costs**: ML can assist in determining the most economical shipping solutions depending on variables such as weight, destination, and delivery time.

• **Higher Sales:** When consumers know exactly when to anticipate their orders, they are more likely to finish their

transactions when provided with clear and accurate delivery information.

• **Proactive Exception Handling:** You may proactively engage with clients and take corrective action to prevent interruptions when possible delays are identified in advance.

## Disadvantages:

While promising, there are also some challenges to consider:

**Data Quality:** The completeness and quality of your data have a significant impact on the accuracy of machine learning models. Predictions that contain missing or inconsistent data may not be trustworthy.

**Model Complexity:** Complex machine learning models demand knowledge and computing power to develop and maintain, which may not be possible for all types of enterprises.

**External Factors:** Variations may arise that machine learning algorithms are not always able to fully capture, such as weather disruptions, carrier problems, or high seasons.

**Costs of Implementation:** There may be upfront expenditure required when integrating machine learning technologies into current systems.

**Over-reliance on Technology:** Although machine learning (ML) is an effective tool, human oversight in the tracking and management of the shipping process shouldn't be replaced by ML.

Overall ,E-commerce shipping prediction with machine learning offers significant advantages for businesses looking to improve customer experience, optimize operations, and gain a competitive edge. However, it's crucial to be aware of the challenges and ensure you have the resources and expertise to implement and maintain an effective ML solution.

## 8.Conclusion

In this study, the possibility of using machine learning to forecast shipping times for online orders was investigated. Using methods for data visualization and analysis, we started by comprehending the data. After that, we preprocessed the data to make sure it was accurate and appropriate for use with machine learning models.

Feature selection strategies were utilized to determine the most pertinent parameters influencing shipping timeframes. This aided in the development of a more precise and effective model. After that, we compared several machine learning models and determined which one performed the best in terms of accuracy

and generalizability.

We learned more about the model's predictive power by assessing its performance on hypothetical data. This study has shown how machine learning may be used to create reasonable shipping expectations and enhance the e-commerce experience for customers.

All things considered, this research has made great progress toward using machine learning to anticipate delivery for e-commerce. We can attain even more accurate shipping predictions by iteratively improving the model and investigating novel strategies. This will increase customer satisfaction and boost the effectiveness of our e-commerce business.

## 9.Future Scope

This project has successfully explored the potential of machine learning for predicting e-commerce shipping times. Here are some exciting avenues for further development:

**1. Advanced Machine Learning Techniques:**

• Examine modeling the sequential nature of the shipping process using recurrent neural networks (RNNs) or long short-term memory (LSTM) networks, which may be able to capture intricate connections between variables.

• Examine how deep learning methods might be included for even more advanced feature extraction and model functionality.

**2. Real-time Data Integration:**

• To increase prediction accuracy, use real-time data feeds from shipment monitoring systems or logistics providers to account for dynamic factors like carrier delays or weather disruptions.

• Create an interactive dashboard that enables proactive exception management and shows anticipated shipment times. This will facilitate quicker customer communication in the event of any delays.

**3. Multimodal Shipping and Personalization:**

• To give clients a more complete view of their options, expand the model to take into account a larger range of shipping options (air, ground, and express), as well as the charges and delivery periods that go along with them.

• For even more individualized arrival estimates, personalize shipping projections by adding customer-specific variables like location, preferred shipping methods, and previous purchase history.

We can advance the field of machine learning-based e-commerce shipment prediction by investigating these potential future avenues. This will result in increased operational efficiency, more precise and dependable shipment estimates, and an informed and contented clientele for e-commerce companies.

# 10. Appendix

## Source code:

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder , StandardScaler, MinMaxScaler
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn import svm
from sklearn.ensemble import RandomForestClassifier
from keras.models import Sequential
from keras.layers import Dense
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report



dataset = pd.read_csv(r"C:\Users\harsha\OneDrive\Desktop\Train.csv")
dataset.head()

dataset.info()

#Checking if there is any null values in the dataset
dataset.isnull().sum()
```

```
#Basic summary statistics
dataset.describe()

delay=pd.DataFrame(dataset.groupby(['Reached.on.Time_Y.N'])['ID'].count()/len(dataset)).reset_index()
plt.pie(delay['ID'],labels=delay['Reached.on.Time_Y.N'],autopct='%1.2f%%')

data_v2=pd.DataFrame((data_v1.groupby(['Mode_of_Shipment'])['ID'].count())/len(data_v1)*100)
data_v2=data_v2.reset_index()
visual=sns.barplot(x="Mode_of_Shipment", y="ID", data=data_v2 )
for index, row in data_v2.iterrows():
    visual.text(row.name,row.ID, round(row.ID,2), color='black', ha="center")
plt.title('Total number of delayed deliveries vs Shipment mode')
plt.ylabel('percentage')

data_v3=pd.DataFrame((data_v1.groupby(['Warehouse_block'])['ID'].count())/len(data_v1)*100)
data_v3=data_v3.reset_index()
visual=sns.barplot(x="Warehouse_block", y="ID", data=data_v3 )
for index, row in data_v3.iterrows():
    visual.text(row.name,row.ID, round(row.ID,2), color='black', ha="center")
plt.title('Total number of delayed deliveries vs Warehouse block')
plt.ylabel('percentage')

data_v4=pd.DataFrame((dataset.groupby(['Customer_rating'])['ID'].count())/len(dataset)*100)
data_v4=data_v4.reset_index()
visual=sns.barplot(x="Customer_rating", y="ID", data=data_v4 )
for index, row in data_v4.iterrows():
    visual.text(row.name,row.ID, round(row.ID,2), color='black', ha="center")
```

```
plt.title('Total percentages of different ratings')
plt.ylabel('percentage')


dataset['Reached.on.Time_Y.N'].replace({1 : "Yes", 0: "No"}, inplace = True)


sns.countplot(x = "Product_importance", data = dataset, hue="Reached.on.Time_Y.N")
plt.title("Product importance by Reached on Time or Not")


sns.countplot(x = "Gender", data = dataset, hue="Reached.on.Time_Y.N")
plt.title("Gender by Reached on Time or Not")


sns.countplot(x = "Warehouse_block", data = dataset, hue = 'Reached.on.Time_Y.N' )
plt.title("Warehouse block vs on Time or Not")


sns.countplot(x = "Customer_rating", data = dataset, hue="Gender")
plt.title("Customer ratings by Gender")


sns.boxplot(x='Gender',y='Cost_of_the_Product',data=dataset,hue='Gender')
plt.title("Amount spent by each Gender")


dataset.groupby(['Product_importance'])['Cost_of_the_Product'].mean().plot.bar()
plt.title("Average cost of products of different importance")


dataset[['Cost_of_the_Product','Prior_purchases','Discount_offered','Weight_in_gms']].hist()
```

## #Handling outliners

```
def check_outliers(arr):
    Q1 = np.percentile(arr, 25, interpolation = 'midpoint')
    Q3 = np.percentile(arr, 75, interpolation = 'midpoint')
```

```
    IQR = Q3 - Q1

#Above Upper bound
    upper=Q3+1.5*IQR
    upper_array=np.array(arr>=upper)
    print(' '*3,len(upper_array[upper_array == True]), 'are over the upper bound:', upper)

    #BeLow Lower bound
    lower=Q1-1.5*IQR
    lower_array=np.array(arr<=lower)
    print(' '*3, len(lower_array[lower_array == True]), 'are less than the lower bound:', lower, '\n')

for i in dataset.drop(columns=[ 'Warehouse_block', 'Mode_of_Shipment', 'Gender',
'Reached.on.Time_Y.N', 'ID' ]).columns:
    if str(dataset[i].dtype)=='object':
        continue
    print(i)
 check_outliers(dataset[i])



from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
y = le.fit_transform(y)

X_train, X_test, y_train, y_test = train_test_split(x,y,test_size=0.3, random_state=42)

#Scaling the data
ms = MinMaxScaler()
X_train = ms.fit_transform(X_train)
X_test = ms.fit_transform(X_test)



svm_model = svm.SVC(gamma='auto',C=5,kernel='rbf')
svm_model.fit(X_train,y_train)
y_pred = svm_model.predict(X_test)
print(classification_report(y_test,y_pred))

from sklearn.linear_model import LogisticRegression

lr=LogisticRegression()
lr.fit(X_train,y_train)
```

```
predLR=lr.predict(X_test)
print(classification_report(y_test,predLR))

from sklearn.tree import DecisionTreeClassifier

df=DecisionTreeClassifier(criterion='entropy',random_state=0)
df.fit(X_train,y_train)
preddf=df.predict(X_test)
print(classification_report(y_test,preddf))

from sklearn.neighbors import KNeighborsClassifier

knn=KNeighborsClassifier()
knn.fit(X_train,y_train)
predknn=knn.predict(X_test)
print(classification_report(y_test,predknn))

from sklearn.naive_bayes import GaussianNB
nb = GaussianNB()

nb.fit(X_train,y_train)
prednb = nb.predict(X_test)
print(classification_report(prednb,y_test))


import xgboost as xgb
xg=xgb.XGBClassifier()
xg.fit(X_train,y_train)
predxg = xg.predict(X_test)
print(classification_report(prednb,y_test))

from sklearn.ensemble import AdaBoostClassifier, GradientBoostingClassifier

ab.fit(X_train,y_train)

gb.fit(X_train,y_train)

pred2= ab.predict(X_test)
pred3= gb.predict(X_test)

print(classification_report(y_test, pred3))
```

```
#Evalution before Tuning

from sklearn.metrics import accuracy_score, f1_score, recall_score, precision_score

def eval(name, model):
   y_pred = model.predict(X_test)
   result = []
   result.append(name)
   result.append("{:.2f}".format(accuracy_score(y_test, y_pred) * 100))
   result.append("{:.2f}".format(f1_score(y_test, y_pred) * 100))
   result.append("{:.2f}".format(recall_score(y_test, y_pred) * 100))
   result.append("{:.2f}".format(precision_score(y_test, y_pred) * 100))
 return result

model_list = {
   'Logistic Regression':lr,
   'XGBoost':xg,
   'Ada Boost':ab,
   'Gradient Boosting' : gb,
   'Support Vector Classifier': svm_model,
   'Naive Bias' : nb,
   'KNN' : knn,
   'Decision Tree' : df,

}


model_eval_info = []
for i in model_list.keys():
   model_eval_info.append(eval(i,model_list[i]))
model_eval_info = pd.DataFrame(model_eval_info, columns=['Name', 'Accuracy', 'fl_score',
'Recall', 'Precision'])
model_eval_info.to_csv('model_eval.csv')
model_eval_info


#Hyper paramerter tuning

params = {'n_estimators':[150,500], 'criterion':['gini', 'entropy'], 'max_depth' : [7],
        'max_features' : [60,80,100]
```

```
        }
#Hyper parameter tuning
rf_model
=GridSearchCV(estimator=RandomForestClassifier(),param_grid=params,scoring='accuracy',
n_jobs = -1, cv=7, verbose = 3)
rf_model.fit(X_train,y_train)
y_pred=rf_model.predict(X_test)
print(classification_report(y_test,y_pred))

params2 = {'min_child_weight' : [10,20],
        'gamma' : [1.5,2.0,2.5],
        'colsample_bytree' : [0.6,0.8,0.9],
        'max_depth' : [4,5,6]
        }
xgb1 = xgb.XGBClassifier(learning_rate=0.5, n_estimators = 100 , objective = 'binary:logistic',
nthread=3)
fitmodelXGB = GridSearchCV(xgb1,param_grid = params2, cv=5, refit = True , scoring =
"accuracy", n_jobs = -1, verbose = 3)
fitmodelXGB.fit(X_train,y_train)
y_pred1=fitmodelXGB.predict(X_test)
print(classification_report(y_test,y_pred1))

lg = LogisticRegression(n_jobs= -1 , random_state = 2)
params3 = {
   'C' : [6,8,10,15,20],
   'max_iter' : [60,80,100]
}
fitmodelLR = GridSearchCV(lg,param_grid = params3, cv=5, refit = True , scoring = "accuracy",
n_jobs = -1, verbose = 3)
fitmodelLR.fit(X_train,y_train)
y_pred2=fitmodelLR.predict(X_test)
print(classification_report(y_test,y_pred2))

print("Best Score:")
print(fitmodelXGB.best_score_)

#Evalution after tuning

def hyper_eval(name, model):
   y_pred_prob = model.predict(X_test)
```

```
    if y_pred_prob.ndim == 2 and y_pred_prob.shape[1] > 1:
        y_pred = y_pred_prob.argmax(axis=1)
    else:
        y_pred = (y_pred_prob >= 0.5).astype(int)  # For binary

    result = []
    result.append(name)
    result.append("{:.2f}".format(accuracy_score(y_test, y_pred) * 100))
    result.append("{:.2f}".format(f1_score(y_test, y_pred, average='weighted') * 100))
    result.append("{:.2f}".format(recall_score(y_test, y_pred, average='weighted') * 100))
    result.append("{:.2f}".format(precision_score(y_test, y_pred, average='weighted') * 100))
    return result

# Example usage:
model_list = {
    'Logistic Regression(Hyper)': fitmodelLR,
    'XGBoost(Hyper)': fitmodelXGB,
    'Random Forest(Hyper)': rf_model,
    'ANN': ann,
}

model_hyper_eval_info = []
for name, model in model_list.items():
    model_hyper_eval_info.append(hyper_eval(name, model))

model_hyper_eval_info = pd.DataFrame(model_hyper_eval_info, columns=['Name', 'Accuracy',
'F1_Score', 'Recall', 'Precision'])
model_hyper_eval_info.to_csv('model_hyper_eval.csv', index=False)
model_hyper_eval_info

#Saving the model

import pickle as pkl

pkl.dump(ms,open('ship_scaler.pkl','wb'))

pkl.dump(le,open('ship_label.pkl','wb'))

import joblib
joblib.dump(ct,"shipct")
```

```
pkl.dump(rf_model,open('Shipping.pkl','wb'))
```

Demo Link:

[Ecommerce Shipping Prediction Using Machine Learning - Made with Clipchamp.mp4 - Google Drive]

Git Link:

https://github.com/sai-Vinayyyyy/E-commerce-shipping-prediction-using-Machine-Learning-.git