Project 2

Group 26

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Classification

Classification Task:

- Apply two voting classifiers - one with hard voting and one with soft voting
- Apply any two models with bagging and any two models with pasting.
- Apply any two models with adaboost boosting
- Apply one model with gradient boosting
- Apply PCA on data and then apply all the models in project 1 again on data you get from PCA. Compare your results with results in project 1. You don't need to apply all the models twice. Just copy the result table from project 1, prepare similar table for all the models after PCA and compare both tables. Does PCA help in getting better results?
- Apply deep learning models covered in class

DataSet

This dataset is taken from kaggel from Global Health Observatory (GHO) data repository under World Health Organization (WHO). It contains hotel booking information and includes information such as for which date booking was made, the lead time,the week night and weekend night stay, the number of adults, children, and/or babies, and the number of available parking spaces etc. There are **1207 total observations** with **19 columns**. Out of this 19 columns we have 6 categorical variables and the target column is with 1 representing a cancellation made and 0 representing no cancellation.

The **target variable** in this is **is_canceled** variable . The model works to predict the life expectancy of a person given his living conditions

Importing necessary libraries for the project

In [1]:
```
#Importing the required libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import GridSearchCV


from sklearn import neighbors
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import r2_score
from math import sqrt
import warnings
warnings.filterwarnings("ignore")
```

Dataset for classification

In [2]:
```
#reading the dataset
df_hotel = pd.read_excel("C:\\Users\\sundh\\Desktop\\ML\\ML_Project1_Group26\\ML Project\\ML Classifica
tion\\hotel_cancel_predictions.xlsx")
#checking the shape of the dataset
df_hotel.shape
```

Out[2]:
```
(1207, 19)
```

Column : Description
is_canceled : Target variable if booking was cancelled
lead_time : No. of days between booking and hotel checkin
arrival_date_month : Month of hotel booking
arrival_date_week_number : Week number of hotel booking
arrival_date_day_of_month : Day of hotel booking
stays_in_weekend_nights : No. of weekend nights stayed
stays_in_week_nights : No. of week nights stayed
adults : No. of adults
children : No. of children
babies : No. of babies
meal : Meal plan booked
market_segment : Market segment of the customer
distribution_channel : distribution channel the customer is in
booking_changes : No. of booking changes made
deposit_type : Deposite type made
days_in_waiting_list : No. of days in waiting for booking
adr : Dollars paid
required_car_parking_spaces : No. of car parking spaces
reservation_status : status of reservation

Exploratory Data Analysis

The exploratory data analysis is performed on the dataset to understand the variations, range, detect outliers and collinearity if it exists in the dataset.

Check for null

Upon checking for null we find that 1728 of the data cells in the dataset have a randomly disbursed null presence

In [3]:
```
#Checking data information
df_hotel.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1207 entries, 0 to 1206
Data columns (total 19 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   is_canceled                  1112 non-null   float64
 1   lead_time                    1132 non-null   float64
 2   arrival_date_month           1120 non-null   object
 3   arrival_date_week_number     1119 non-null   float64
 4   arrival_date_day_of_month    1097 non-null   float64
 5   stays_in_weekend_nights      1111 non-null   float64
 6   stays_in_week_nights         1114 non-null   float64
 7   adults                       1116 non-null   float64
 8   children                     1117 non-null   float64
 9   babies                       1124 non-null   float64
 10  meal                         1118 non-null   object
 11  market_segment               1125 non-null   object
 12  distribution_channel         1107 non-null   object
 13  booking_changes              1110 non-null   float64
 14  deposit_type                 1117 non-null   object
 15  days_in_waiting_list         1114 non-null   float64
 16  adr                          1117 non-null   float64
 17  required_car_parking_spaces  1127 non-null   float64
 18  reservation_status           1108 non-null   object
dtypes: float64(13), object(6)
memory usage: 179.3+ KB
```

There are totally 19 columns with more than two categorical columns

In [4]:
```
#Total count of null
df_hotel.isna().sum().sum()
```

Out[4]:
```
1728
```

In [5]:
```
#Count of null by column
df_hotel.isna().sum()
```

Out[5]:
```
is_canceled                     95
lead_time                       75
arrival_date_month              87
arrival_date_week_number        88
arrival_date_day_of_month      110
stays_in_weekend_nights         96
stays_in_week_nights            93
adults                          91
children                        90
babies                          83
meal                            89
market_segment                  82
distribution_channel           100
booking_changes                 97
deposit_type                    90
days_in_waiting_list            93
adr                             90
required_car_parking_spaces     80
reservation_status              99
dtype: int64
```

To handle the null we check the data in the first five rows

In [6]:
```
#reading the first five rows in the dataset
df_hotel.head()
```

Out[6]:

	is_canceled	lead_time	arrival_date_month	arrival_date_week_number	arrival_date_day_of_month	stays_in_weekend_nights	stays_in_w
0	0.0	26.0	March	12.0	17.0	2.0	
1	1.0	NaN	October	44.0	28.0	2.0	
2	0.0	0.0	April	16.0	12.0	0.0	
3	0.0	0.0	May	21.0	NaN	1.0	
4	0.0	138.0	NaN	13.0	NaN	0.0	

Handle Null To handle the null, we choose to impute the mean value of the numeric columns and for categorical variables we have imputed the value with most count

In [7]:
```
#Fill NULL with mean of the column data
df_hotel['is_canceled'].fillna(df_hotel['is_canceled'].mean(), inplace=True)
df_hotel['lead_time'].fillna(df_hotel['lead_time'].mean(), inplace=True)
df_hotel['arrival_date_day_of_month'].fillna(df_hotel['arrival_date_day_of_month'].mean(), inplace=True
)
df_hotel['stays_in_weekend_nights'].fillna(df_hotel['stays_in_weekend_nights'].mean(), inplace=True)
df_hotel['stays_in_week_nights'].fillna(df_hotel['stays_in_week_nights'].mean(), inplace=True)
df_hotel['adults'].fillna(df_hotel['adults'].mean(), inplace=True)
df_hotel['children'].fillna(df_hotel['children'].mean(), inplace=True)
df_hotel['adr'].fillna(df_hotel['adr'].mean(), inplace=True)
df_hotel['booking_changes'].fillna(df_hotel['booking_changes'].mean(), inplace=True)
df_hotel['market_segment'].fillna(df_hotel['market_segment'].value_counts().index[0], inplace=True)
df_hotel['arrival_date_week_number'].fillna(df_hotel['arrival_date_week_number'].mean(), inplace=True)
df_hotel['arrival_date_month'].fillna(df_hotel['arrival_date_month'].value_counts().index[0], inplace=T
rue)
df_hotel['babies'].fillna(df_hotel['babies'].mean(), inplace=True)
df_hotel['meal'].fillna(df_hotel['meal'].value_counts().index[0], inplace=True)
df_hotel['distribution_channel'].fillna(df_hotel['distribution_channel'].value_counts().index[0], inpla
ce=True)
df_hotel['required_car_parking_spaces'].fillna(df_hotel['required_car_parking_spaces'].mean(), inplace=
True)
df_hotel['reservation_status'].fillna(df_hotel['reservation_status'].value_counts().index[0], inplace=T
rue)
df_hotel['days_in_waiting_list'].fillna(df_hotel['days_in_waiting_list'].mean(), inplace=True)
df_hotel['deposit_type'].fillna(df_hotel['deposit_type'].value_counts().index[0], inplace=True)
```

We check to see if all the columns have 0 null presence

In [8]:
```
#checking for nulls in each column
df_hotel.isna().sum()
```

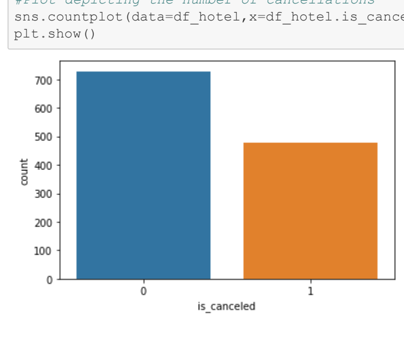
Out[8]:
```
is_canceled                    0
lead_time                      0
arrival_date_month             0
arrival_date_week_number       0
arrival_date_day_of_month      0
stays_in_weekend_nights        0
stays_in_week_nights           0
adults                         0
children                       0
babies                         0
meal                           0
market_segment                 0
distribution_channel           0
booking_changes                0
deposit_type                   0
days_in_waiting_list           0
adr                            0
required_car_parking_spaces    0
reservation_status             0
dtype: int64
```

In [9]:
```
#Changing the datatype from float to integer
df_hotel['lead_time']=df_hotel['lead_time'].astype(int)
df_hotel['arrival_date_day_of_month']=df_hotel['arrival_date_day_of_month'].astype(int)
df_hotel['stays_in_weekend_nights']=df_hotel['stays_in_weekend_nights'].astype(int)
df_hotel['stays_in_week_nights']=df_hotel['stays_in_week_nights'].astype(int)
df_hotel['stays_in_weekend_nights']=df_hotel['stays_in_weekend_nights'].astype(int)
df_hotel['adults']=df_hotel['adults'].astype(int)
df_hotel['children']=df_hotel['children'].astype(int)
df_hotel['booking_changes']=df_hotel['booking_changes'].astype(int)
df_hotel['is_canceled']=df_hotel['is_canceled'].astype(int)
```

Data Visualisation

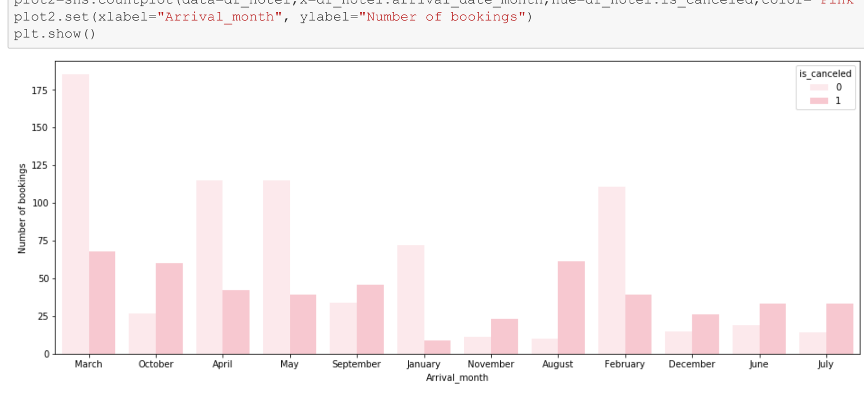
We check the spread of the target variable is_canceled. We see that most of the hotel bookings in our dataset are not canceled.

In [10]:
```
#Plot depicting the number of cancellations
sns.countplot(data=df_hotel,x=df_hotel.is_canceled)
plt.show()
```



Visualising the spread of cancellations and booking over the months. It can be seen that most of the bookings done in March are not cancelled and August has least booking. Maximum booking cancellation are also done in March with least in January

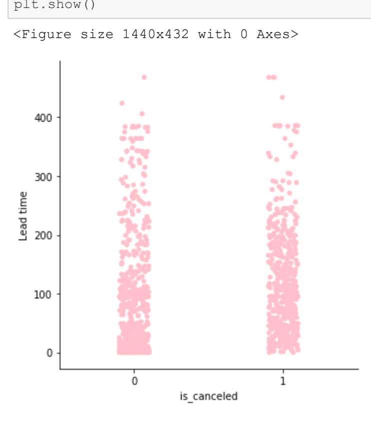
In [11]:
```
#Plotting number of cancellations and confirmed bookings done month-wise
plt.figure(figsize=(16, 6))
plot2=sns.countplot(data=df_hotel,x=df_hotel.arrival_date_month,hue=df_hotel.is_canceled,color='Pink')
plot2.set(xlabel="Arrival_month", ylabel="Number of bookings")
plt.show()
```



Checking the presence of outliera in is_canceled with respect to the lead time which is the number of days between the booking made and the date of hotel stay We find that as the lead days increases, the outliers are present in both cancelled as well as confirmed bookings. But we dont remove these to as it would be the case in real time data

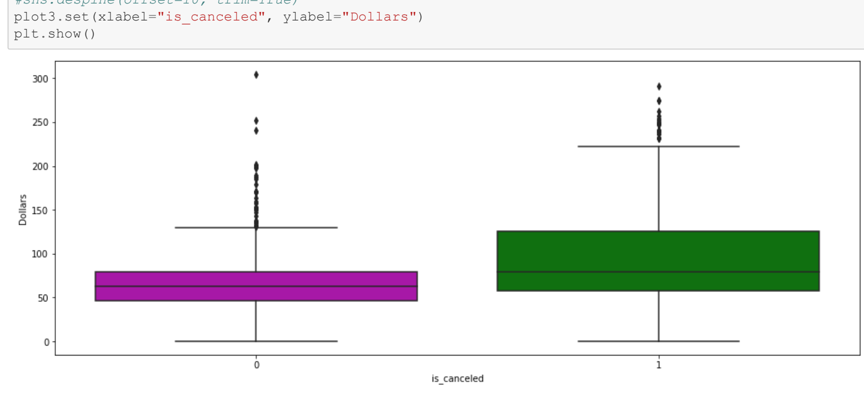
In [12]:
```
#PLotting the scatterplot of lead times of canceled and confirmed bookings
plt.figure(figsize=(20, 6))
plot2=sns.catplot(data=df_hotel,x='is_canceled',y='lead_time',color='Pink')#,order=[0,1]
plot2.set(xlabel="is_canceled", ylabel="Lead time")
plt.show()
```

```
<Figure size 1440x432 with 0 Axes>
```



Cancelled a booking always puts a hole in the pocket. We can see the variation in the dollars spent in this case.

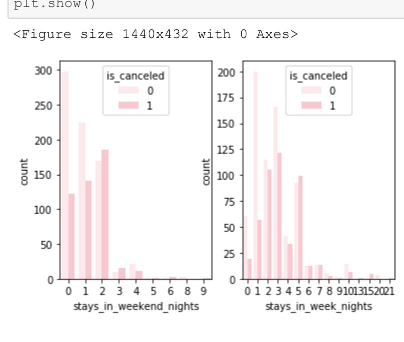
In [13]:
```
# Plotting the box plot depicting the dollar amount spent for canceled and confirmed bookings
plt.figure(figsize=(16, 6))
plot3=sns.boxplot(data=df_hotel,x='is_canceled', y='adr',
            palette=["m", "g"])
#sns.despine(offset=10, trim=True)
plot3.set(xlabel="is_canceled", ylabel="Dollars")
plt.show()
```



Weekends are always for getaways and sometime it ends up with a spoiler. This can be seen in the plot below showing that cancellations are more in weekend night stays as people tentatively make a booking

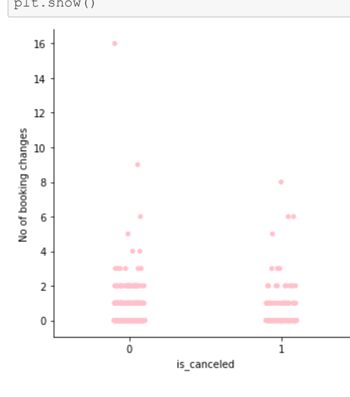
In [14]:
```
#Plotting the count of canceled and confirmed bookings having weekend and week nights
plt.figure(figsize=(20, 6))
fig, ax =plt.subplots(1,2)
sns.countplot(data=df_hotel,x='stays_in_weekend_nights',hue='is_canceled',color='Pink', ax=ax[0])
sns.countplot(data=df_hotel,x='stays_in_week_nights',hue='is_canceled',color='Pink', ax=ax[1])
plt.show()
```

```
<Figure size 1440x432 with 0 Axes>
```



The number of changes made to a booking are visualised and can be infered that people who dont cancel make more changes to their bookings

In [15]:
```
#Plotting the booking changes done for canceled and confirmed bookings
plot2=sns.catplot(data=df_hotel,x='is_canceled',y='booking_changes',color='Pink')
plot2.set(xlabel="is_canceled", ylabel="No of booking changes")
plt.show()
```

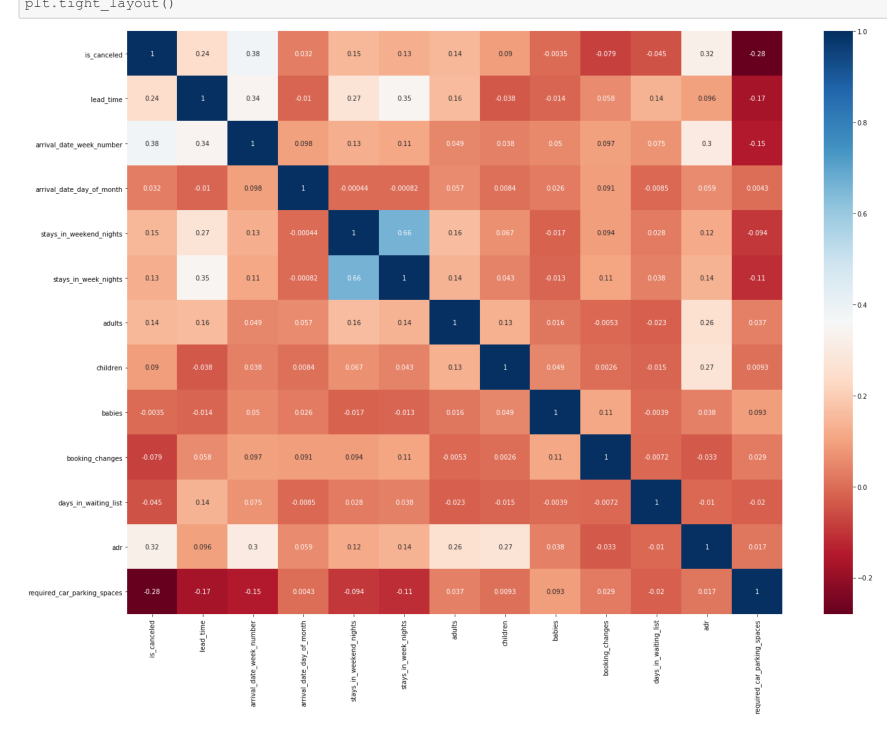


When no deposit is expected upfront to make a booking, people are seen to book more and cancel it as well

In [16]:
```
#Plotting the deposit type for confirmed and canceled bookings
plt.figure(figsize=(16, 6))
plot2=sns.countplot(data=df_hotel,x='deposit_type',hue='is_canceled',color='Pink')
plot2.set(xlabel="Deposit type", ylabel="Number of bookings")
plt.show()
```

We check for correlation among the variables

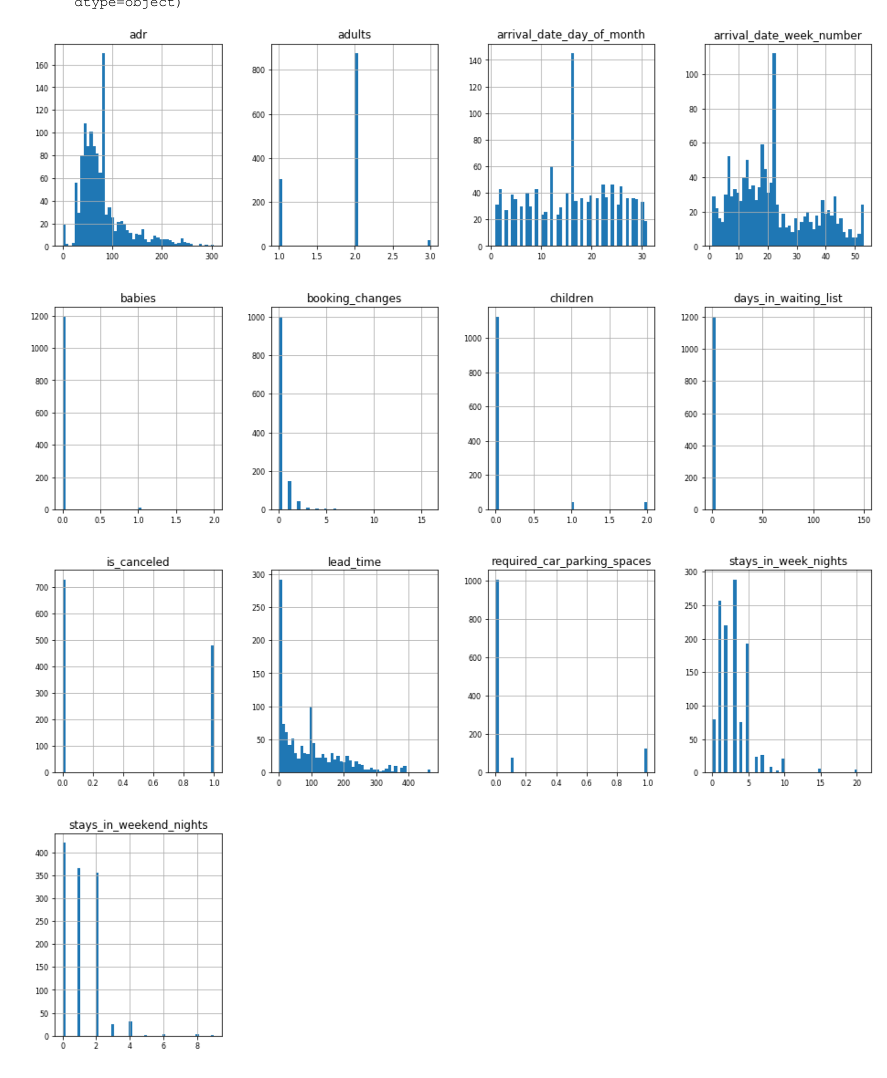
In [17]:
```
# Making Correlation Matrix to find the relations between the variables
plt.figure(figsize=(20,15))
sns.heatmap(df_hotel.corr(), cmap='RdBu', annot=True)
plt.tight_layout()
```



Distribution of all variables

In [18]:
```
#Further exploration using histogram to check the distributions
df_hotel.hist(figsize=(16, 20), bins=50, xlabelsize=8, ylabelsize=8)
```

Out[18]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x000001D1CB2B2388>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001D1CB2BCBC8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001D1CABE7808>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001D1CAC20948>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x000001D1CAC58A48>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001D1CAC91B08>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001D1CB20C288>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001D1CA8FD088>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x000001D1CA91D588>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001D1CA78DAC8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001D1C9A3D948>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001D1C99A2A88>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x000001D1C99B3908>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001D1C9994188>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001D1C999A408>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001D1CB21B248>]],
      dtype=object)
```



Handle categorical variables

The categorical variables need to be converted to dummy variables which add more columns. Categorical variables will be represented as 0 or 1 in the columns

In [19]:
```
#creating dummies for arrival_date_month column
cols = pd.get_dummies(df_hotel['arrival_date_month'], prefix= 'arrival_month')
df_hotel[cols.columns] = cols
df_hotel.drop('arrival_date_month', axis = 1, inplace = True)
```

In [20]:
```
#creating dummies for meal column
cols = pd.get_dummies(df_hotel['meal'], prefix= 'meal')
df_hotel[cols.columns] = cols
df_hotel.drop('meal', axis = 1, inplace = True)
```

In [21]:
```
#creating dummies for market_segment column
cols = pd.get_dummies(df_hotel['market_segment'], prefix= 'market_segment')
df_hotel[cols.columns] = cols
df_hotel.drop('market_segment', axis = 1, inplace = True)
```

In [22]:
```
#creating dummies for deposit_type column
cols = pd.get_dummies(df_hotel['deposit_type'], prefix= 'deposit_type')
df_hotel[cols.columns] = cols
df_hotel.drop('deposit_type', axis = 1, inplace = True)
```

In [23]:
```
#creating dummies for arrival_date_month column
cols = pd.get_dummies(df_hotel['distribution_channel'], prefix= 'distribution_channel')
df_hotel[cols.columns] = cols
df_hotel.drop('distribution_channel', axis = 1, inplace = True)
```

In [24]:
```
#creating dummies for reservation_status column
cols = pd.get_dummies(df_hotel['reservation_status'], prefix= 'reservation_status')
df_hotel[cols.columns] = cols
df_hotel.drop('reservation_status', axis = 1, inplace = True)
```

In [25]:
```
#reading the first five rows in the dataset
df_hotel.head()
```

Out[25]:

	is_canceled	lead_time	arrival_date_week_number	arrival_date_day_of_month	stays_in_weekend_nights	stays_in_week_nights	adults
0	0	26	12.0	17	2	3	2
1	1	95	44.0	28	2	5	2
2	0	0	16.0	12	0	5	1
3	0	0	21.0	16	1	1	2
4	0	138	13.0	16	0	3	2

5 rows × 44 columns

In [26]:
```
df_hotel.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1207 entries, 0 to 1206
Data columns (total 44 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   is_canceled                     1207 non-null   int32
 1   lead_time                       1207 non-null   int32
 2   arrival_date_week_number        1207 non-null   float64
 3   arrival_date_day_of_month       1207 non-null   int32
 4   stays_in_weekend_nights         1207 non-null   int32
 5   stays_in_week_nights            1207 non-null   int32
 6   adults                          1207 non-null   int32
 7   children                        1207 non-null   int32
 8   babies                          1207 non-null   float64
 9   booking_changes                 1207 non-null   int32
 10  days_in_waiting_list            1207 non-null   float64
 11  adr                             1207 non-null   float64
 12  required_car_parking_spaces     1207 non-null   float64
 13  arrival_month_April             1207 non-null   uint8
 14  arrival_month_August            1207 non-null   uint8
 15  arrival_month_December          1207 non-null   uint8
 16  arrival_month_February          1207 non-null   uint8
 17  arrival_month_January           1207 non-null   uint8
 18  arrival_month_July              1207 non-null   uint8
 19  arrival_month_June              1207 non-null   uint8
 20  arrival_month_March             1207 non-null   uint8
 21  arrival_month_May               1207 non-null   uint8
 22  arrival_month_November          1207 non-null   uint8
 23  arrival_month_October           1207 non-null   uint8
 24  arrival_month_September         1207 non-null   uint8
 25  meal_BB                         1207 non-null   uint8
 26  meal_FB                         1207 non-null   uint8
 27  meal_HB                         1207 non-null   uint8
 28  meal_Undefined                  1207 non-null   uint8
 29  market_segment_Complementary    1207 non-null   uint8
 30  market_segment_Corporate        1207 non-null   uint8
 31  market_segment_Direct           1207 non-null   uint8
 32  market_segment_Groups           1207 non-null   uint8
 33  market_segment_Offline TA/TO    1207 non-null   uint8
 34  market_segment_Online TA        1207 non-null   uint8
 35  deposit_type_No Deposit         1207 non-null   uint8
 36  deposit_type_Non Refund         1207 non-null   uint8
 37  deposit_type_Refundable         1207 non-null   uint8
 38  distribution_channel_Corporate  1207 non-null   uint8
 39  distribution_channel_Direct     1207 non-null   uint8
 40  distribution_channel_TA/TO      1207 non-null   uint8
 41  reservation_status_Canceled     1207 non-null   uint8
 42  reservation_status_Check-Out    1207 non-null   uint8
 43  reservation_status_No-Show      1207 non-null   uint8
dtypes: float64(5), int32(8), uint8(31)
memory usage: 121.5 KB
```

In [27]:
```
#Checking the final list of columns
for col in df_hotel.columns:
    print(col)
```

```
is_canceled
lead_time
arrival_date_week_number
arrival_date_day_of_month
stays_in_weekend_nights
stays_in_week_nights
adults
children
babies
booking_changes
days_in_waiting_list
adr
required_car_parking_spaces
arrival_month_April
arrival_month_August
arrival_month_December
arrival_month_February
arrival_month_January
arrival_month_July
arrival_month_June
arrival_month_March
arrival_month_May
arrival_month_November
arrival_month_October
arrival_month_September
meal_BB
meal_FB
meal_HB
meal_Undefined
market_segment_Complementary
market_segment_Corporate
market_segment_Direct
market_segment_Groups
market_segment_Offline TA/TO
market_segment_Online TA
deposit_type_No Deposit
deposit_type_Non Refund
deposit_type_Refundable
distribution_channel_Corporate
distribution_channel_Direct
distribution_channel_TA/TO
reservation_status_Canceled
reservation_status_Check-Out
reservation_status_No-Show
```

In [28]:
```
#checking the number of nulls in each column
df_hotel.isna().sum()
```

Out[28]:
```
is_canceled                       0
lead_time                         0
arrival_date_week_number          0
arrival_date_day_of_month         0
stays_in_weekend_nights           0
stays_in_week_nights              0
adults                            0
children                          0
babies                            0
booking_changes                   0
days_in_waiting_list              0
adr                               0
required_car_parking_spaces       0
arrival_month_April               0
arrival_month_August              0
arrival_month_December            0
arrival_month_February            0
arrival_month_January             0
arrival_month_July                0
arrival_month_June                0
arrival_month_March               0
arrival_month_May                 0
arrival_month_November            0
arrival_month_October             0
arrival_month_September           0
meal_BB                           0
meal_FB                           0
meal_HB                           0
meal_Undefined                    0
market_segment_Complementary      0
market_segment_Corporate          0
market_segment_Direct             0
market_segment_Groups             0
market_segment_Offline TA/TO      0
market_segment_Online TA          0
deposit_type_No Deposit           0
deposit_type_Non Refund           0
deposit_type_Refundable           0
distribution_channel_Corporate    0
distribution_channel_Direct       0
distribution_channel_TA/TO        0
reservation_status_Canceled       0
reservation_status_Check-Out      0
reservation_status_No-Show        0
dtype: int64
```

In [29]:
```
#Checking the number of rows and columns
df_hotel.shape
```

Out[29]:
```
(1207, 44)
```

Train and Test Split

The test and train split is done with 0.2

In [30]:
```
#X and y split
y = df_hotel['is_canceled'].values
X = df_hotel.drop(['is_canceled'], axis = 1).values
```

In [31]:
```
#test and train split
X_train, X_test, y_train, y_test = train_test_split(X, y,random_state=0,test_size=0.2)
```

```
In [32]: #checking X values
         X
```

```
Out[32]: array([[ 26.,  12.,  17., ...,   0.,   1.,   0.],
                [ 95.,  44.,  28., ...,   1.,   0.,   0.],
                [  0.,  16.,  12., ...,   0.,   1.,   0.],
                ...,
                [112.,  39.,  19., ...,   0.,   1.,   0.],
                [ 32.,  35.,  27., ...,   0.,   1.,   0.],
                [106.,  17.,  23., ...,   1.,   0.,   0.]])
```

Scaling

Scaling is done with MinMax scaler which scales the data with respect to the minimum and maximum values, this is better than the standard scaler which will mostly incline towards the mean of the data.

```
In [33]: # Scaling the dataset
         #through histogram we see that data is not much normally distributed for some of the columns.
         #Hence we use Standard Scaler to normalize and scale
         from sklearn.preprocessing import MinMaxScaler
         scaler = MinMaxScaler()
         X_train = scaler.fit_transform(X_train)
         X_test = scaler.transform(X_test)
```

```
In [34]: Classification_Scores={}
```

1) Voting Classifier

Voting is an ensemble classifier which is a combination from multiple machine learning algorithms.It helps in lowering error and lessen over-fitting

```
In [35]: from sklearn.ensemble import VotingClassifier
         from sklearn.linear_model import LogisticRegression
         from sklearn.svm import SVC
         from sklearn.tree import DecisionTreeClassifier
```

Hard voting : Case where the class with more votes are selected

a) Voting Classifier - Hard

Logistic regression is run with c=1 , penalty set as l2 and liblinear solver is used.

SVM poly kernel is run with gamma=0.1, c=1

KNN with neighbor = 9 is run

These models are used with voting to find a best model with highest votes

```
In [36]: logistic_clf = LogisticRegression(C=1, penalty= 'l2',solver='liblinear')
         svc_clf = SVC(kernel = 'poly', gamma = 0.1, C=1, probability=True)
         knn_clf=KNeighborsClassifier(9)
```

Train data is fit into the different models without voting

```
In [37]: logistic_clf.fit(X_train, y_train)
         svc_clf.fit(X_train, y_train)
         #decisiontree_clf.fit(X_train, y_train)
         knn_clf.fit(X_train,y_train)
```

```
Out[37]: KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                              metric_params=None, n_jobs=None, n_neighbors=9, p=2,
                              weights='uniform')
```

Voting is done with the three models

```
In [38]: voting = VotingClassifier(estimators=[('lr', logistic_clf), ('svc', svc_clf), ('kn', knn_clf)], voting
         = 'hard')
```

The scores of the training set of the models are shown:

```
In [39]: print('log_clf: ', logistic_clf.score(X_train, y_train))
         print('svc_clf: ', svc_clf.score(X_train, y_train))
         print('kn_clf: ', knn_clf.score(X_train, y_train))
```

```
log_clf:  0.9461139896373058
svc_clf:  0.9471502590673575
kn_clf:  0.938860103626943
```

The train and test score for the voting classifier is obtained

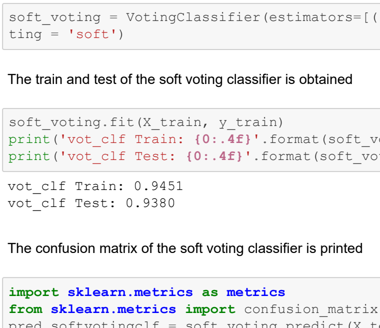
```
In [40]: voting.fit(X_train, y_train)
         print('vot_clf Train:{0:.4f}'.format(voting.score(X_train, y_train)))
         print('vot_clf Test: {0:.4f}'.format(voting.score(X_test, y_test)))
```

```
vot_clf Train:0.9482
vot_clf Test: 0.9380
```

Confusion matrix is printed with values of the voting classifier

```
In [41]: import sklearn.metrics as metrics
         from sklearn.metrics import confusion_matrix, classification_report
         pred_hardvotingclf = voting.predict(X_test)
         print(metrics.accuracy_score(y_test,pred_hardvotingclf))

         confusion = confusion_matrix(y_test, pred_hardvotingclf)
         import seaborn as sns
         import matplotlib.pyplot as plt

         ax= plt.subplot()
         sns.heatmap(confusion, annot=True,fmt='d', ax = ax); #annot=True to annotate cells

         # labels, title and ticks
         ax.set_xlabel('Predicted labels')
         ax.set_ylabel('True labels')

         print(classification_report(y_test,pred_hardvotingclf))
```

```
0.9380165289256198
              precision    recall  f1-score   support

           0       0.95      0.95      0.95       151
           1       0.92      0.91      0.92        91

    accuracy                           0.94       242
   macro avg       0.93      0.93      0.93       242
weighted avg       0.94      0.94      0.94       242
```



The F1 score and Recall is obtained

```
In [42]: from sklearn.metrics import precision_recall_fscore_support as score

         precision,recall,fscore,support=score(y_test,pred_hardvotingclf)

         print ('Recall    : {}'.format(recall[0]))
         print ('F1Score    : {}'.format(fscore[0]))
```

```
Recall    : 0.9536423841059603
F1Score    : 0.9504950495049505
```

```
In [43]: Classification_Scores.update({'Hard voting Classifier':[metrics.accuracy_score(y_test,pred_hardvotingcl
         f),recall[0],fscore[0]]})
```

b) Voting Classifier - Soft

Soft voting is done with probability vector of each class summed and averaged

```
In [44]: soft_voting = VotingClassifier(estimators=[('lr', logistic_clf), ('svc', svc_clf), ('kn', knn_clf)], vo
         ting = 'soft')
```

The train and test of the soft voting classifier is obtained

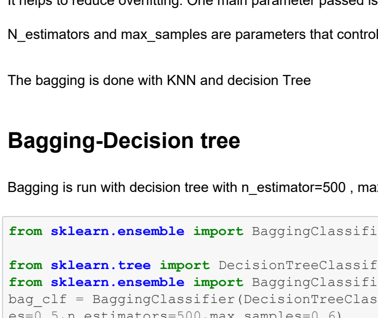
```
In [45]: soft_voting.fit(X_train, y_train)
         print('vot_clf Train: {0:.4f}'.format(soft_voting.score(X_train, y_train)))
         print('vot_clf Test: {0:.4f}'.format(soft_voting.score(X_test, y_test)))
```

```
vot_clf Train: 0.9451
vot_clf Test: 0.9380
```

The confusion matrix of the soft voting classifier is printed

```
In [46]: import sklearn.metrics as metrics
         from sklearn.metrics import confusion_matrix, classification_report
         pred_softvotingclf = soft_voting.predict(X_test)
         print(metrics.accuracy_score(y_test,pred_softvotingclf))

         confusion = confusion_matrix(y_test, pred_softvotingclf)
         import seaborn as sns
         import matplotlib.pyplot as plt

         ax= plt.subplot()
         sns.heatmap(confusion, annot=True,fmt='d', ax = ax); #annot=True to annotate cells

         # labels, title and ticks
         ax.set_xlabel('Predicted labels')
         ax.set_ylabel('True labels')


         print(classification_report(y_test,pred_softvotingclf))
```

```
0.9380165289256198
              precision    recall  f1-score   support

           0       0.95      0.95      0.95       151
           1       0.92      0.91      0.92        91

    accuracy                           0.94       242
   macro avg       0.93      0.93      0.93       242
weighted avg       0.94      0.94      0.94       242
```



The F1 score and Recall values are obtained

```
In [47]: from sklearn.metrics import precision_recall_fscore_support as score

         precision,recall,fscore,support=score(y_test,pred_softvotingclf)

         print ('Recall    : {}'.format(recall[0]))
         print ('F1Score    : {}'.format(fscore[0]))
```

```
Recall    : 0.9536423841059603
F1Score    : 0.9504950495049505
```

```
In [48]: Classification_Scores.update({'Soft voting calssifier':[metrics.accuracy_score(y_test,pred_softvotingcl
         f),recall[0],fscore[0]]})
```

2)Bagging

Bagging is an aggregation ensemble meta-algorithm designed to improve the stability and accuracy of algorithms.

It helps to reduce overfitting. One main parameter passed is the bootstrap parameter.It uses sampling with replacement.

N_estimators and max_samples are parameters that control the number of decision trees and sample size used.

The bagging is done with KNN and decision Tree

Bagging-Decision tree

Bagging is run with decision tree with n_estimator=500 , max_features=0.5

```
In [49]: from sklearn.ensemble import BaggingClassifier

         from sklearn.tree import DecisionTreeClassifier
         from sklearn.ensemble import BaggingClassifier
         bag_clf = BaggingClassifier(DecisionTreeClassifier(),bootstrap=True,n_jobs=-1,random_state=0,max_featur
         es=0.5,n_estimators=500,max_samples=0.6)

         bag_clf.fit(X_train, y_train)
         print("Accuracy on training set: {:.3f}".format(bag_clf.score(X_train, y_train)))
         print("Accuracy on test set: {:.3f}".format(bag_clf.score(X_test, y_test)))
```

```
Accuracy on training set: 0.977
Accuracy on test set: 0.942
```

Cross validation score for the bagging classifier

```
In [50]: scores = cross_val_score(bag_clf, X_train, y_train, cv = 10, scoring = 'accuracy' )
         print("Cross-validation scores: {}".format(scores))

         print("Average cross-validation score: {:.2f}".format(scores.mean()))
```

```
Cross-validation scores: [0.93814433 0.95876289 0.88659794 0.96907216 0.96907216 0.91666667
 0.94791667 0.88541667 0.97916667 0.94791667]
Average cross-validation score: 0.94
```

Grid Search is done with max_samples, max_features and n_estimators to find the best parameters

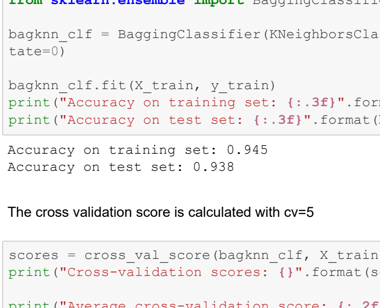
```
In [51]: param_grid = {'max_samples': [0.5,0.6,0.8],
                      'max_features': [0.4,0.5,0.6],
                      'n_estimators': [100,300,500]}

         grid_search_bagclf = GridSearchCV(BaggingClassifier(random_state=0,bootstrap=True,n_jobs=-1), param_gri
         d, cv=5, return_train_score=True)

         grid_search_bagclf.fit(X_train, y_train)

         print("Best parameters: {}".format(grid_search_bagclf.best_params_))
         print("Best cross-validation score: {:.2f}".format(grid_search_bagclf.best_score_))
```

```
Best parameters: {'max_features': 0.5, 'max_samples': 0.6, 'n_estimators': 500}
Best cross-validation score: 0.94
```

Confusion matrix is printed for the above classifier

```
In [52]: import sklearn.metrics as metrics
         from sklearn.metrics import confusion_matrix, classification_report
         pred_bagclf = grid_search_bagclf.predict(X_test)
         print(metrics.accuracy_score(y_test,pred_bagclf))

         confusion = confusion_matrix(y_test, pred_bagclf)
         import seaborn as sns
         import matplotlib.pyplot as plt

         ax= plt.subplot()
         sns.heatmap(confusion, annot=True,fmt='d', ax = ax); #annot=True to annotate cells

         # labels, title and ticks
         ax.set_xlabel('Predicted labels')
         ax.set_ylabel('True labels')


         print(classification_report(y_test,pred_bagclf))
```

```
0.9421487603305785
              precision    recall  f1-score   support

           0       0.95      0.95      0.95       151
           1       0.92      0.92      0.92        91

    accuracy                           0.94       242
   macro avg       0.94      0.94      0.94       242
weighted avg       0.94      0.94      0.94       242
```



The Recall and F1 score for the decision tree with bagging is obtained

```
In [53]: from sklearn.metrics import precision_recall_fscore_support as score

         precision,recall,fscore,support=score(y_test,pred_bagclf)

         print ('Recall    : {}'.format(recall[0]))
         print ('F1Score    : {}'.format(fscore[0]))
```

```
Recall    : 0.9536423841059603
F1Score    : 0.9536423841059603
```

```
In [54]: Classification_Scores.update({'Bagging-Decision Tree Classifier':[metrics.accuracy_score(y_test,pred_ba
         gclf),recall[0],fscore[0]]})
```

Bagging - KNN

The KNN model is run with neighbors = 4 with bagging

```
In [55]: from sklearn.ensemble import BaggingClassifier

         bagknn_clf = BaggingClassifier(KNeighborsClassifier(n_neighbors=4), bootstrap=True, n_jobs=-1, random_s
         tate=0)

         bagknn_clf.fit(X_train, y_train)
         print("Accuracy on training set: {:.3f}".format(bagknn_clf.score(X_train, y_train)))
         print("Accuracy on test set: {:.3f}".format(bagknn_clf.score(X_test, y_test)))
```

```
Accuracy on training set: 0.945
Accuracy on test set: 0.938
```

The cross validation score is calculated with cv=5

```
In [56]: scores = cross_val_score(bagknn_clf, X_train, y_train, cv = 5, scoring = 'accuracy' )
         print("Cross-validation scores: {}".format(scores))

         print("Average cross-validation score: {:.2f}".format(scores.mean()))
```

```
Cross-validation scores: [0.93264249 0.89119171 0.94818653 0.9119171  0.94818653]
Average cross-validation score: 0.93
```

Grid search is used to find the best parameters for max_sample, max_features and n_estimators

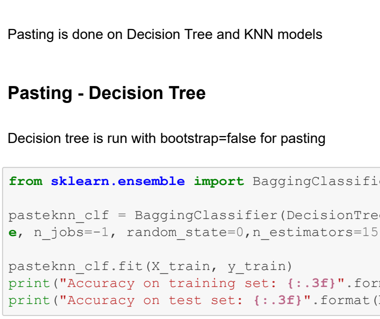
```
In [57]: param_grid = {'max_samples': [0.5,0.6],
                      'max_features': [0.4,0.5],
                      'n_estimators': [100,500]}

         grid_search_bagclfknn = GridSearchCV(BaggingClassifier(KNeighborsClassifier(n_neighbors=4),random_state
         =0,bootstrap=True,n_jobs=-1), param_grid, cv=5, return_train_score=True)

         grid_search_bagclfknn.fit(X_train, y_train)

         print("Best parameters: {}".format(grid_search_bagclf.best_params_))
         print("Best cross-validation score: {:.2f}".format(grid_search_bagclf.best_score_))
```

```
Best parameters: {'max_features': 0.5, 'max_samples': 0.6, 'n_estimators': 500}
Best cross-validation score: 0.94
```

Confusion matrix is printed

```
In [58]: import sklearn.metrics as metrics
         from sklearn.metrics import confusion_matrix, classification_report
         pred_bagknn_clf = grid_search_bagclfknn.predict(X_test)
         print(metrics.accuracy_score(y_test,pred_bagknn_clf))

         confusion = confusion_matrix(y_test, pred_bagknn_clf)
         import seaborn as sns
         import matplotlib.pyplot as plt

         ax= plt.subplot()
         sns.heatmap(confusion, annot=True,fmt='d', ax = ax); #annot=True to annotate cells

         # labels, title and ticks
         ax.set_xlabel('Predicted labels')
         ax.set_ylabel('True labels')
         #ax.xaxis.set_ticklabels(['Attrition', 'No-Attrition'])
         #ax.yaxis.set_ticklabels(['Attrition', 'No-Attrition'])

         print(classification_report(y_test,pred_bagknn_clf))
```

```
0.9380165289256198
              precision    recall  f1-score   support

           0       0.95      0.95      0.95       151
           1       0.92      0.91      0.92        91

    accuracy                           0.94       242
   macro avg       0.93      0.93      0.93       242
weighted avg       0.94      0.94      0.94       242
```



The Recall and F1 score is calculated

```
In [59]: from sklearn.metrics import precision_recall_fscore_support as score

         precision,recall,fscore,support=score(y_test,pred_bagknn_clf)

         print ('Recall    : {}'.format(recall[0]))
         print ('F1Score    : {}'.format(fscore[0]))
```

```
Recall    : 0.9536423841059603
F1Score    : 0.9504950495049505
```

```
In [60]: Classification_Scores.update({'Bagging-KNN Classifier':[metrics.accuracy_score(y_test,pred_bagknn_clf),
         recall[0],fscore[0]]})
```

3)Pasting

Pasting is an aggregation ensemble meta-algorithm designed to improve the stability and accuracy of algorithms. It helps to reduce overfitting. One main parameter passed is the bootstrap parameter which is set to false.It uses sampling without replacement.

N_estimators and max_samples are parameters that control the number of decision trees and sample size used.

Pasting is done on Decision Tree and KNN models

Pasting - Decision Tree

Decision tree is run with bootstrap=false for pasting

```
In [61]: from sklearn.ensemble import BaggingClassifier

         pasteknn_clf = BaggingClassifier(DecisionTreeClassifier(random_state = 0, max_depth= 2), bootstrap=Fals
         e, n_jobs=-1, random_state=0,n_estimators=150,max_samples=100)

         pasteknn_clf.fit(X_train, y_train)
         print("Accuracy on training set: {:.3f}".format(bagknn_clf.score(X_train, y_train)))
         print("Accuracy on test set: {:.3f}".format(bagknn_clf.score(X_test, y_test)))
```

```
Accuracy on training set: 0.945
Accuracy on test set: 0.938
```

Cross validation is done on the model with cv=10

```
In [62]: scores = cross_val_score(bagknn_clf, X_train, y_train, cv = 10, scoring = 'accuracy' )
         print("Cross-validation scores: {}".format(scores))

         print("Average cross-validation score: {:.2f}".format(scores.mean()))
```

```
Cross-validation scores: [0.91752577 0.95876289 0.87628866 0.89690722 0.97938144 0.91666667
 0.91666667 0.88541667 0.95833333 0.9375    ]
Average cross-validation score: 0.92
```

The gridsearch is used to find best parameters for max_samples, max_features and n_estimators for the decision tree

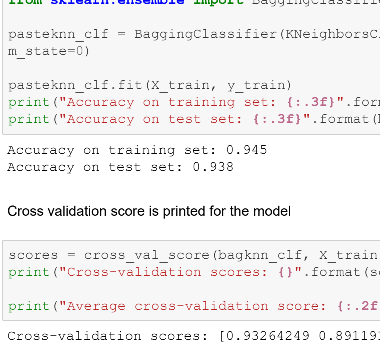
```
In [63]: param_grid = {'max_samples': [0.5,0.6],
                      'max_features': [0.4,0.5],
                      'n_estimators': [100,500]}

         grid_search_pasteknnclf = GridSearchCV(BaggingClassifier(DecisionTreeClassifier(max_depth= 2),random_st
         ate=0,bootstrap=False,n_jobs=-1), param_grid, cv=5, return_train_score=True)

         grid_search_pasteknnclf.fit(X_train, y_train)

         print("Best parameters: {}".format(grid_search_pasteknnclf.best_params_))
         print("Best cross-validation score: {:.2f}".format(grid_search_pasteknnclf.best_score_))
```

```
Best parameters: {'max_features': 0.4, 'max_samples': 0.5, 'n_estimators': 500}
Best cross-validation score: 0.95
```

Confusion matrix is printed with the model outcome

```
In [64]: import sklearn.metrics as metrics
         from sklearn.metrics import confusion_matrix, classification_report
         pred_pasteclf = pasteknn_clf.predict(X_test)
         print(metrics.accuracy_score(y_test,pred_pasteclf))

         confusion = confusion_matrix(y_test, pred_pasteclf)
         import seaborn as sns
         import matplotlib.pyplot as plt

         ax= plt.subplot()
         sns.heatmap(confusion, annot=True, fmt='d',ax = ax); #annot=True to annotate cells

         # labels
         ax.set_xlabel('Predicted labels')
         ax.set_ylabel('True labels')
         print(classification_report(y_test,pred_pasteclf))
```

```
0.9380165289256198
              precision    recall  f1-score   support

           0       0.95      0.95      0.95       151
           1       0.92      0.91      0.92        91

    accuracy                           0.94       242
   macro avg       0.93      0.93      0.93       242
weighted avg       0.94      0.94      0.94       242
```



The recall and F1 score of the model is printed

```
In [65]: from sklearn.metrics import precision_recall_fscore_support as score

         precision,recall,fscore,support=score(y_test,pred_pasteclf)

         print ('Recall    : {}'.format(recall[0]))
         print ('F1Score    : {}'.format(fscore[0]))
```

```
Recall    : 0.9536423841059603
F1Score    : 0.9504950495049505
```

```
In [66]: Classification_Scores.update({'Pasting-Decision Tree':[metrics.accuracy_score(y_test,pred_pasteclf),rec
         all[0],fscore[0]]})
```

Pasting - KNN

KNN classfier with Pasting is modelled with bootstrap=false

```
In [67]: from sklearn.ensemble import BaggingClassifier

         pasteknn_clf = BaggingClassifier(KNeighborsClassifier(n_neighbors=4), bootstrap=False, n_jobs=-1, rando
         m_state=0)

         pasteknn_clf.fit(X_train, y_train)
         print("Accuracy on training set: {:.3f}".format(bagknn_clf.score(X_train, y_train)))
         print("Accuracy on test set: {:.3f}".format(bagknn_clf.score(X_test, y_test)))
```

```
Accuracy on training set: 0.945
Accuracy on test set: 0.938
```

Cross validation score is printed for the model

```
In [68]: scores = cross_val_score(bagknn_clf, X_train, y_train, cv = 5, scoring = 'accuracy' )
         print("Cross-validation scores: {}".format(scores))

         print("Average cross-validation score: {:.2f}".format(scores.mean()))
```

```
Cross-validation scores: [0.93264249 0.89119171 0.94818653 0.9119171  0.94818653]
Average cross-validation score: 0.93
```

Gridsearch is used to find the best parameters for max_samples, max_features and n_estimators are found

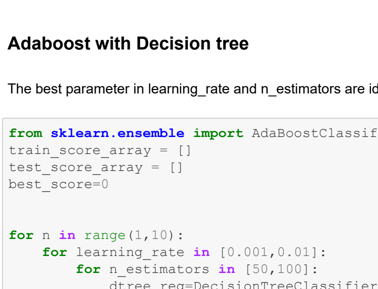
```
In [69]: param_grid = {'max_samples': [0.5,0.6],
                      'max_features': [0.4,0.5],
                      'n_estimators': [100,500]}

         grid_search_pasteknnclf = GridSearchCV(BaggingClassifier(KNeighborsClassifier(),random_state=0,bootstra
         p=False,n_jobs=-1), param_grid, cv=5, return_train_score=True)

         grid_search_pasteknnclf.fit(X_train, y_train)

         print("Best parameters: {}".format(grid_search_pasteknnclf.best_params_))
         print("Best cross-validation score: {:.2f}".format(grid_search_pasteknnclf.best_score_))
```

```
Best parameters: {'max_features': 0.4, 'max_samples': 0.5, 'n_estimators': 500}
Best cross-validation score: 0.94
```

Confusion matrix is printed for the model

```
In [70]: import sklearn.metrics as metrics
         from sklearn.metrics import confusion_matrix, classification_report
         pred_pasteclf = pasteknn_clf.predict(X_test)
         print(metrics.accuracy_score(y_test,pred_pasteclf))

         confusion = confusion_matrix(y_test, pred_pasteclf)
         import seaborn as sns
         import matplotlib.pyplot as plt

         ax= plt.subplot()
         sns.heatmap(confusion, annot=True,fmt='d', ax = ax); #annot=True to annotate cells

         # labels, title and ticks
         ax.set_xlabel('Predicted labels')
         ax.set_ylabel('True labels')

         print(classification_report(y_test,pred_pasteclf))
```

```
0.9380165289256198
              precision    recall  f1-score   support

           0       0.95      0.95      0.95       151
           1       0.91      0.92      0.92        91

    accuracy                           0.94       242
   macro avg       0.93      0.94      0.93       242
weighted avg       0.94      0.94      0.94       242
```



Recall and F1 score are printed

```
In [71]: from sklearn.metrics import precision_recall_fscore_support as score

         precision,recall,fscore,support=score(y_test,pred_pasteclf)

         print ('Recall    : {}'.format(recall[0]))
         print ('F1Score    : {}'.format(fscore[0]))
```

```
Recall    : 0.9470198675496688
F1Score    : 0.9501661129568105
```

```
In [72]: Classification_Scores.update({'Pasting-KNN Classifier':[metrics.accuracy_score(y_test,pred_pasteclf),re
         call[0],fscore[0]]})
```

AdaBoosting

Adaboost turns multiple weak classifiers into a strong classifier. The important parameters used are n_estimators and learning_rate.

Learning rate shrinks the contribution of each classifier by learning_rate chosen.

Adaboost with Decision tree

The best parameter in learning_rate and n_estimators are identified

```
In [73]: from sklearn.ensemble import AdaBoostClassifier
         train_score_array = []
         test_score_array = []
         best_score=0


         for n in range(1,10):
             for learning_rate in [0.001,0.01]:
                 for n_estimators in [50,100]:
                     dtree_reg=DecisionTreeClassifier(max_depth=n)
                     ada_reg_dtree = AdaBoostClassifier(dtree_reg, n_estimators=n_estimators,learning_rate=learn
         ing_rate,random_state=0)
                     ada_reg_dtree.fit(X_train, y_train)
                     train_score_array.append(ada_reg_dtree.score(X_train, y_train))
                     test_score_array.append(ada_reg_dtree.score(X_test, y_test))
                     score=ada_reg_dtree.score(X_test, y_test)
                     if(score>best_score):
                         best_score=score
                         best_parameters = {'learning_rate': learning_rate, 'max_depth': n,'n_estimators':n_esti
         mators}

         print(best_parameters)
```

```
{'learning_rate': 0.01, 'max_depth': 5, 'n_estimators': 50}
```

The train and test score for the decision tree model with max_depth =5 and n_estimator=50, learning_rate=0.01

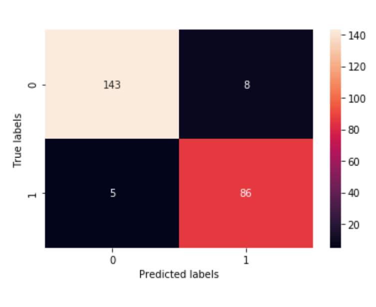
```
In [74]: from sklearn.ensemble import AdaBoostClassifier

         dt_reg = DecisionTreeClassifier(max_depth=5,random_state=0)
         ada_reg_dt = AdaBoostClassifier(dt_reg, n_estimators=50,learning_rate=0.01,random_state=0)

         ada_reg_dt.fit(X_train,y_train)

         y_pred=ada_reg_dt.predict(X_test)

         print('Train score: {:.4f} %'.format(ada_reg_dt.score(X_train, y_train)*100))
         print('Test score: {:.4f} %'.format(ada_reg_dt.score(X_test, y_test)*100))
```

```
Train score: 98.5492 %
Test score: 94.6281 %
```

Confusion matrix is printed

```
In [75]: pred_ada = ada_reg_dt.predict(X_test)
         print(metrics.accuracy_score(y_test,pred_ada))

         confusion = confusion_matrix(y_test, pred_ada)
         import seaborn as sns
         import matplotlib.pyplot as plt

         ax= plt.subplot()
         sns.heatmap(confusion, annot=True,fmt='d', ax = ax); #annot=True to annotate cells

         # labels, title and ticks
         ax.set_xlabel('Predicted labels')
         ax.set_ylabel('True labels')

         print(classification_report(y_test,pred_ada))
```

```
0.9462809917355371
              precision    recall  f1-score   support

           0       0.97      0.95      0.96       151
           1       0.91      0.95      0.93        91

    accuracy                           0.95       242
   macro avg       0.94      0.95      0.94       242
weighted avg       0.95      0.95      0.95       242
```



Recall and F1 score is calculated

```
In [76]: from sklearn.metrics import precision_recall_fscore_support as score

         precision,recall,fscore,support=score(y_test,pred_ada)

         print ('Recall    : {}'.format(recall[0]))
         print ('F1Score    : {}'.format(fscore[0]))
```

```
Recall    : 0.9470198675496688
F1Score    : 0.9565217391304347
```

```
In [77]: Classification_Scores.update({'Adaboosting-Decision Tree':[metrics.accuracy_score(y_test,pred_ada),reca
ll[0],fscore[0]]})
```

Adaboost with SVC Poly

Kernel =poly, n_estimators=200 and learning_rate=0.1 are used for SVC poly model with adaboost

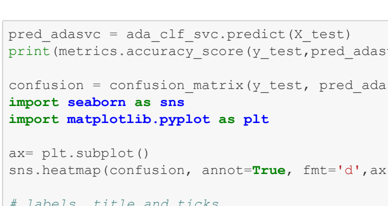
```
In [78]: from sklearn.svm import SVC
svc_clf=SVC(C=1,gamma=0.1, kernel='poly',probability=True)
ada_clf_svc = AdaBoostClassifier(svc_clf, n_estimators=200,learning_rate=0.1,random_state=0)
ada_clf_svc.fit(X_train, y_train)

y_pred=ada_clf_svc.predict(X_test)
print('Train score: {:.4f} %'.format(ada_clf_svc.score(X_train, y_train)*100))
print('Test score: {:.4f} %'.format(ada_clf_svc.score(X_test, y_test)*100))
```

```
Train score: 93.8860 %
Test score: 90.9091 %
```

Confusion matrix is printed for the above model

```
In [79]: pred_adasvc = ada_clf_svc.predict(X_test)
print(metrics.accuracy_score(y_test,pred_adasvc))

confusion = confusion_matrix(y_test, pred_adasvc)
import seaborn as sns
import matplotlib.pyplot as plt

ax= plt.subplot()
sns.heatmap(confusion, annot=True, fmt='d',ax = ax); #annot=True to annotate cells

# labels, title and ticks
ax.set_xlabel('Predicted labels')
ax.set_ylabel('True labels')

print(classification_report(y_test,pred_adasvc))
```

```
0.9090909090909091
              precision    recall  f1-score   support

           0       0.91      0.95      0.93       151
           1       0.91      0.85      0.87        91

    accuracy                           0.91       242
   macro avg       0.91      0.90      0.90       242
weighted avg       0.91      0.91      0.91       242
```




```
In [80]: from sklearn.metrics import precision_recall_fscore_support as score

precision,recall,fscore,support=score(y_test,pred_adasvc)

print ('Recall    : {}'.format(recall[0]))
print ('F1Score    : {}'.format(fscore[0]))
```

```
Recall    : 0.9470198675496688
F1Score    : 0.9285714285714285
```

```
In [81]: Classification_Scores.update({'Adaboosting-SVC Poly Classifier':[metrics.accuracy_score(y_test,pred_ada
svc),recall[0],fscore[0]]})
```

Gradient Boosting

Gradient boosting is a technique which minimizes the overall prediction error. The key idea is to set the target outcomes for the next best model in order to minimize the error. Gradient boosting model is primarily used with decision tree.

The key parameters used are n_estimators and learning_rate

```
In [82]: from  sklearn.ensemble import GradientBoostingClassifier

gradient_boosting = GradientBoostingClassifier(max_depth=2, random_state=0)
param_grid={'n_estimators':[50,100,150],'learning_rate':[0.5,1]}
grid7=GridSearchCV(gradient_boosting,param_grid,cv=5,return_train_score=True)
grid7.fit(X_train, y_train)
train7=grid7.cv_results_['mean_train_score']
print("Best Parameters: {}".format(grid7.best_params_))
print("Train score: {0:.3f}".format(train7.mean()))
print("Test score: {0:.3f}".format(grid7.score(X_test,y_test)))
```

```
Best Parameters: {'learning_rate': 0.5, 'n_estimators': 50}
Train score: 0.994
Test score: 0.909
```

The best params learning_rate=0.5 and n_estimators:20 are used with max_depth=2 for decision tree

```
In [83]: grad_clf = GradientBoostingClassifier(max_depth=2, n_estimators=50,learning_rate=0.5,random_state=0)
grad_clf.fit(X_train, y_train)

y_pred=grad_clf.predict(X_test)
```

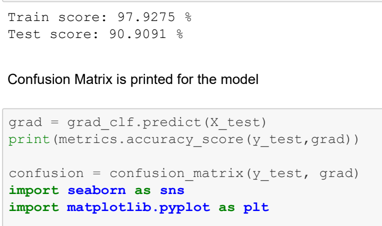
```
In [84]: print('Train score: {:.4f} %'.format(grad_clf.score(X_train, y_train)*100))
print('Test score: {:.4f} %'.format(grad_clf.score(X_test, y_test)*100))
```

```
Train score: 97.9275 %
Test score: 90.9091 %
```

Confusion Matrix is printed for the model

```
In [85]: grad = grad_clf.predict(X_test)
print(metrics.accuracy_score(y_test,grad))

confusion = confusion_matrix(y_test, grad)
import seaborn as sns
import matplotlib.pyplot as plt

ax= plt.subplot()
sns.heatmap(confusion, annot=True, fmt='d',ax = ax); #annot=True to annotate cells

# labels, title and ticks
ax.set_xlabel('Predicted labels')
ax.set_ylabel('True labels')


print(classification_report(y_test,grad))
```

```
0.9090909090909091
              precision    recall  f1-score   support

           0       0.91      0.95      0.93       151
           1       0.91      0.85      0.87        91

    accuracy                           0.91       242
   macro avg       0.91      0.90      0.90       242
weighted avg       0.91      0.91      0.91       242
```




```
In [86]: from sklearn.metrics import precision_recall_fscore_support as score

precision,recall,fscore,support=score(y_test,grad)

print ('Recall    : {}'.format(recall[0]))
print ('F1Score    : {}'.format(fscore[0]))
```

```
Recall    : 0.9470198675496688
F1Score    : 0.9285714285714285
```

```
In [87]: Classification_Scores.update({'Gradient boosting':[metrics.accuracy_score(y_test,grad),recall[0],fscore
[0]]})
```

Random Forest

The random forest is a classifier consisting of many decisions trees

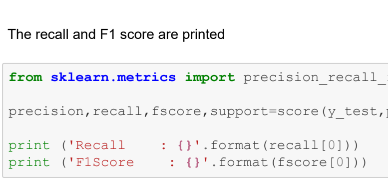
```
In [88]: from sklearn.ensemble import RandomForestClassifier

forest = RandomForestClassifier(random_state=0)
forest.fit(X_train, y_train)

print("Accuracy on training set: {:.3f}".format(forest.score(X_train, y_train)))
print("Accuracy on test set: {:.3f}".format(forest.score(X_test, y_test)))
```

```
Accuracy on training set: 0.997
Accuracy on test set: 0.938
```

Confusion Matrix is generated

```
In [89]: import sklearn.metrics as metrics
from sklearn.metrics import confusion_matrix, classification_report
pred_forestclf = forest.predict(X_test)
print(metrics.accuracy_score(y_test,pred_forestclf))

confusion = confusion_matrix(y_test, pred_forestclf)
import seaborn as sns
import matplotlib.pyplot as plt

ax= plt.subplot()
sns.heatmap(confusion, annot=True, fmt='d',ax = ax); #annot=True to annotate cells

# labels, title and ticks
ax.set_xlabel('Predicted labels')
ax.set_ylabel('True labels')

print(classification_report(y_test,pred_forestclf))
```

```
0.9380165289256198
              precision    recall  f1-score   support

           0       0.95      0.95      0.95       151
           1       0.92      0.91      0.92        91

    accuracy                           0.94       242
   macro avg       0.93      0.93      0.93       242
weighted avg       0.94      0.94      0.94       242
```



The recall and F1 score are printed

```
In [90]: from sklearn.metrics import precision_recall_fscore_support as score

precision,recall,fscore,support=score(y_test,pred_forestclf)

print ('Recall    : {}'.format(recall[0]))
print ('F1Score    : {}'.format(fscore[0]))
```

```
Recall    : 0.9536423841059603
F1Score    : 0.9504950495049505
```

```
In [91]: Classification_Scores.update({'Random Forest':[metrics.accuracy_score(y_test,pred_forestclf),recall[0],
fscore[0]]})
```

```
In [92]: forest.feature_importances_
```

```
Out[92]: array([0.0629187 , 0.06364299, 0.02162273, 0.01250533, 0.02042624,
       0.00529865, 0.00404272, 0.00353806, 0.00871052, 0.00425258,
       0.04741042, 0.02148329, 0.00285393, 0.00668045, 0.00122707,
       0.00173329, 0.00176495, 0.00229307, 0.00082871, 0.00435428,
       0.0019443 , 0.00645337, 0.00466284, 0.00269751, 0.00331846,
       0.00221829, 0.00220869, 0.00113739, 0.00128925, 0.00165149,
       0.00361966, 0.0095361 , 0.00724962, 0.00976158, 0.00791325,
       0.01682447, 0.00158011, 0.00061867, 0.00340788, 0.00454487,
       0.28132018, 0.32447714, 0.00397691])
```

PCA

PCA is statistical technique using dimensionality reduction with sole basis that large number of features add to high dimensionality which essentially leads to overfitting.

PCA thus reduces the number of feautures taken into consideration.

```
In [93]: from sklearn.decomposition import PCA

# intialize pca and logistic regression model
pca = PCA(n_components=0.95)
```

```
In [94]: X_train_pca= pca.fit_transform(X_train)
X_test_pca = pca.transform(X_test)

print(X_train_pca.shape)
print(y_train.shape)
print(X_test_pca.shape)
print(y_test.shape)
```

```
(965, 24)
(965,)
(242, 24)
(242,)
```

PCA is run on all the models

KNN with PCA

KNN classifier is modeled with cv=5 and the cross val score is calculated

GridSearch is used to find the best neighbor that can be used

```
In [95]: k_range = list(range(1, 11))

param_grid = dict(n_neighbors=k_range)

grid_search_knn = GridSearchCV(KNeighborsClassifier(), param_grid, cv=5, return_train_score=True)

grid_search_knn.fit(X_train_pca, y_train)

df = pd.DataFrame(grid_search_knn.cv_results_)
%matplotlib inline
x_axis = range(1,11)
plt.plot(x_axis, df.mean_train_score, c = 'g', label = 'Train Score')
plt.plot(x_axis, df.mean_test_score, c = 'b', label = 'Validation Score')
plt.legend()
plt.xlabel('k')
plt.ylabel('CV Score')

print("Best parameters: {}".format(grid_search_knn.best_params_))
print("Best cross-validation score: {:.2f}".format(grid_search_knn.best_score_))
```

```
Best parameters: {'n_neighbors': 5}
Best cross-validation score: 0.93
```

Neighbour=5 is taken for the KNN classifier

```
In [96]: knn = KNeighborsClassifier(n_neighbors=5)
knn.fit(X_train_pca, y_train)
print('Train score on best parameters {:.4f}'.format(knn.score(X_train_pca,y_train)))
print('Test score on best parameters {:.4f}'.format(knn.score(X_test_pca,y_test)))
```

```
Train score on best parameters 0.9461
Test score on best parameters 0.9380
```

Cross validation score for the KNN is found

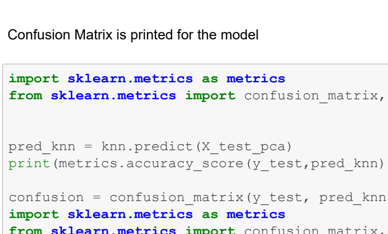
```
In [97]: from sklearn.model_selection import cross_val_score
from sklearn.model_selection import GridSearchCV
knn_grid = KNeighborsClassifier(5)

scores = cross_val_score(knn_grid, X_train_pca, y_train, cv =5, scoring = 'accuracy')
print("Cross-validation scores: {}".format(scores))

print("Average cross-validation score: {:.2f}".format(scores.mean()))
```

```
Cross-validation scores: [0.94818653 0.91709845 0.94300518 0.92227979 0.93782383]
Average cross-validation score: 0.93
```

Confusion Matrix is printed for the model

```
In [98]: import sklearn.metrics as metrics
from sklearn.metrics import confusion_matrix, classification_report


pred_knn = knn.predict(X_test_pca)
print(metrics.accuracy_score(y_test,pred_knn))

confusion = confusion_matrix(y_test, pred_knn)
import sklearn.metrics as metrics
from sklearn.metrics import confusion_matrix, classification_report
import seaborn as sns
import matplotlib.pyplot as plt

ax= plt.subplot()
sns.heatmap(confusion, annot=True, fmt='d',ax = ax); #annot=True to annotate cells

# labels, title and ticks
ax.set_xlabel('Predicted labels')
ax.set_ylabel('True labels')

print(classification_report(y_test,pred_knn))
```

```
0.9380165289256198
              precision    recall  f1-score   support

           0       0.95      0.95      0.95       151
           1       0.91      0.92      0.92        91

    accuracy                           0.94       242
   macro avg       0.93      0.94      0.93       242
weighted avg       0.94      0.94      0.94       242
```



Recall and F1 score is printed

```
In [99]: from sklearn.metrics import precision_recall_fscore_support as score

precision,recall,fscore,support=score(y_test,pred_knn)

print ('Recall    : {}'.format(recall[0]))
print ('F1Score    : {}'.format(fscore[0]))
```

```
Recall    : 0.9470198675496688
F1Score    : 0.9501661129568105
```

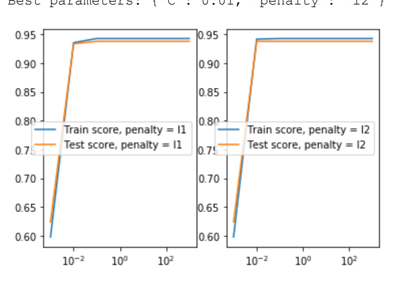
```
In [100]: Classification_Scores.update({'KNN Classification with PCA':[metrics.accuracy_score(y_test,pred_knn),r
ecall[0],fscore[0]]})
```

Logistic reg after PCA

Logistic regression is run after the PCA is done on the dataset

```
In [101]: # import warnings filter
from warnings import simplefilter
# ignore all future warnings
simplefilter(action='ignore', category=FutureWarning)

from sklearn.linear_model import LogisticRegression

c_range = [0.001, 0.01, 0.1, 1, 10, 100, 1000]
train_score_l1 = []
train_score_l2 = []
valid_score_l1 = []
valid_score_l2 = []

best_score = 0
l1 = 'l1'
l2 = 'l2'

for c in c_range:
    log_l1 = LogisticRegression(penalty = 'l1', C = c,solver='liblinear')
    log_l2 = LogisticRegression(penalty = 'l2', C = c,solver='lbfgs')

    log_l1.fit(X_train_pca, y_train)
    log_l2.fit(X_train_pca, y_train)

    train_score_l1.append(log_l1.score(X_train_pca, y_train))
    train_score_l2.append(log_l2.score(X_train_pca, y_train))

    score = log_l1.score(X_test_pca, y_test)
    valid_score_l1.append(score)
    if score > best_score:
            best_score = score
            best_parameters = {'C': c , 'penalty': l1}
            best_C = c
            best_Penalty = 'l1'

    score = log_l2.score(X_test_pca, y_test)
    valid_score_l2.append(score)
    if score > best_score:
            best_score = score
            best_parameters = {'C': c , 'penalty' : l2}
            best_C = c
            best_Penalty = 'l2'

plt.subplot(1,2,1)
plt.plot(c_range, train_score_l1, label = 'Train score, penalty = l1')
plt.plot(c_range, valid_score_l1, label = 'Test score, penalty = l1')
plt.xscale('log')
plt.legend()
plt.subplot(1,2,2)
plt.plot(c_range, train_score_l2, label = 'Train score, penalty = l2')
plt.plot(c_range, valid_score_l2, label = 'Test score, penalty = l2')
plt.xscale('log')
plt.legend()

print("Best score: {:.2f}".format(best_score))
print("Best parameters: {}".format(best_parameters))
```

```
Best score: 0.94
Best parameters: {'C': 0.01, 'penalty': 'l2'}
```



Train and test score are calculated

```
In [102]: lg = LogisticRegression(C=0.01,penalty='l2').fit(X_train_pca, y_train)
print('Train score on best parameters for Logistic Regression model {:.4f}'.format(lg.score(X_train_pc
a,y_train)))
print('Test score on best parameters for Logistic Regression model {:.4f}'.format(lg.score(X_test_pca,
y_test)))
```

```
Train score on best parameters for Logistic Regression model 0.9420
Test score on best parameters for Logistic Regression model 0.9380
```

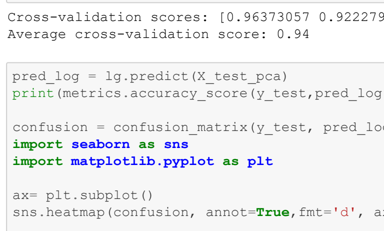
Logistic regression is modelled with penalty L2 and C=0.01

```
In [103]: log_grid = LogisticRegression(penalty = 'l2', C = 0.01)

scores = cross_val_score(log_grid, X_train_pca, y_train, cv =5, scoring = 'accuracy')
print("Cross-validation scores: {}".format(scores))

print("Average cross-validation score: {:.2f}".format(scores.mean()))
```

```
Cross-validation scores: [0.96373057 0.92227979 0.93782383 0.9119171  0.97409326]
Average cross-validation score: 0.94
```

```
In [104]: pred_log = lg.predict(X_test_pca)
print(metrics.accuracy_score(y_test,pred_log))

confusion = confusion_matrix(y_test, pred_log)
import seaborn as sns
import matplotlib.pyplot as plt

ax= plt.subplot()
sns.heatmap(confusion, annot=True,fmt='d', ax = ax); #annot=True to annotate cells

# labels, title and ticks
ax.set_xlabel('Predicted labels')
ax.set_ylabel('True labels')

print(classification_report(y_test,pred_log))
```

```
0.9380165289256198
              precision    recall  f1-score   support

           0       0.95      0.95      0.95       151
           1       0.92      0.91      0.92        91

    accuracy                           0.94       242
   macro avg       0.93      0.93      0.93       242
weighted avg       0.94      0.94      0.94       242
```




```
In [105]: from sklearn.metrics import precision_recall_fscore_support as score

precision,recall,fscore,support=score(y_test,pred_log)

print ('Recall    : {}'.format(recall[0]))
print ('F1Score    : {}'.format(fscore[0]))
```

```
Recall    : 0.9536423841059603
F1Score    : 0.9504950495049505
```

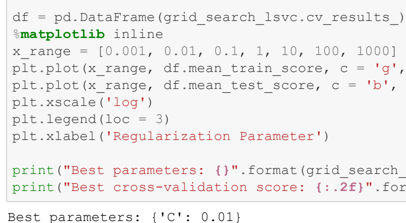
```
In [106]: Classification_Scores.update({'Logistic Regression with PCA':[metrics.accuracy_score(y_test,pred_log),
recall[0],fscore[0]]})
```

Linear SVC with PCA

Linear SVC is modeled with with grid search for best param for C

```
In [107]: from sklearn.svm import LinearSVC
param_grid = {'C': [0.001, 0.01, 0.1, 1, 10, 100, 1000]}
grid_search_lsvc = GridSearchCV(LinearSVC(max_iter=100000000), param_grid, cv=5, return_train_score=Tr
ue)

grid_search_lsvc.fit(X_train_pca, y_train)

df = pd.DataFrame(grid_search_lsvc.cv_results_)
%matplotlib inline
x_range = [0.001, 0.01, 0.1, 1, 10, 100, 1000]
plt.plot(x_range, df.mean_train_score, c = 'g', label = 'Train Score')
plt.plot(x_range, df.mean_test_score, c = 'b', label = 'Validation Score')
plt.xscale('log')
plt.legend(loc = 3)
plt.xlabel('Regularization Parameter')

print("Best parameters: {}".format(grid_search_lsvc.best_params_))
print("Best cross-validation score: {:.2f}".format(grid_search_lsvc.best_score_))
```

```
Best parameters: {'C': 0.01}
Best cross-validation score: 0.94
```



The train and test score are calculated for this model

```
In [108]: from sklearn.svm import SVC
clf1 = SVC(kernel='linear', C=0.01).fit(X_train_pca, y_train)
print('Train score on best parameters for LinearSVC - {:.4f}'.format(clf1.score(X_train_pca, y_train
)))
print('Test score on best parameters ffor LinearSVC - {:.4f}'.format(clf1.score(X_test_pca,y_test)))
```

```
Train score on best parameters for LinearSVC - 0.9440
Test score on best parameters ffor LinearSVC - 0.9380
```

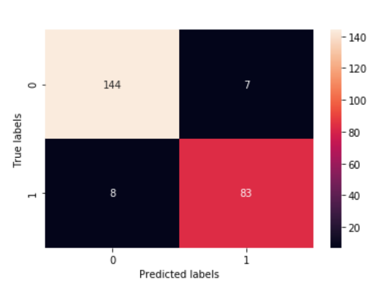
```
In [109]: linear_svc_grid = LinearSVC(C = 0.01, max_iter=10000)
scores = cross_val_score(linear_svc_grid, X_train_pca, y_train, cv = 5, scoring = 'accuracy')
print("Cross-validation scores: {}".format(scores))

print("Average cross-validation score: {:.2f}".format(scores.mean()))
```

```
Cross-validation scores: [0.96373057 0.92227979 0.94300518 0.91709845 0.97409326]
Average cross-validation score: 0.94
```

Confusion Matrix is printed

```
In [110]: pred_linear_svc = clf1.predict(X_test_pca)
print(metrics.accuracy_score(y_test,pred_linear_svc))

confusion = confusion_matrix(y_test, pred_linear_svc)
import seaborn as sns
import matplotlib.pyplot as plt

ax= plt.subplot()
sns.heatmap(confusion, annot=True,fmt='d', ax = ax); #annot=True to annotate cells

# labels, title and ticks
ax.set_xlabel('Predicted labels')
ax.set_ylabel('True labels')

print(classification_report(y_test,pred_linear_svc))
```

```
0.9380165289256198
              precision    recall  f1-score   support

           0       0.95      0.95      0.95       151
           1       0.92      0.91      0.92        91

    accuracy                           0.94       242
   macro avg       0.93      0.93      0.93       242
weighted avg       0.94      0.94      0.94       242
```



RECALL and F1 score are printed

```
In [111]: from sklearn.metrics import precision_recall_fscore_support as score

precision,recall,fscore,support=score(y_test,pred_linear_svc)

print ('Recall    : {}'.format(recall[0]))
print ('F1Score    : {}'.format(fscore[0]))
```

```
Recall    : 0.9536423841059603
F1Score    : 0.9504950495049505
```

```
In [112]: Classification_Scores.update({'Linear SVC with PCA':[metrics.accuracy_score(y_test,pred_linear_svc),re
call[0],fscore[0]]})
```

SVC-rbf pca

Gridsearch is used to find the best param of gamma and C

```
In [113]: param_grid = {'gamma': [0.001, 0.01, 0.1, 1, 10, 100],
              'C': [0.001, 0.01, 0.1, 1, 10, 100]}

grid_search_svcr = GridSearchCV(SVC(kernel='rbf'), param_grid, cv=5, return_train_score=True)

grid_search_svcr.fit(X_train_pca, y_train)

df = pd.DataFrame(grid_search_svcr.cv_results_)
print("Best parameters: {}".format(grid_search_svcr.best_params_))
print("Best cross-validation score: {:.2f}".format(grid_search_svcr.best_score_))
```

```
Best parameters: {'C': 0.1, 'gamma': 0.1}
Best cross-validation score: 0.95
```

The best param of C=0.1 and gamma=0.1 are used

```
In [114]: clf2 = SVC(kernel='rbf', C=0.1,gamma=0.1).fit(X_train_pca, y_train)
print('Train score on best parameters for LinearSVC - {:.4f}'.format(clf1.score(X_train_pca, y_train
)))
print('Test score on best parameters ffor LinearSVC - {:.4f}'.format(clf1.score(X_test_pca,y_test)))
```

```
Train score on best parameters for LinearSVC - 0.9440
Test score on best parameters ffor LinearSVC - 0.9380
```

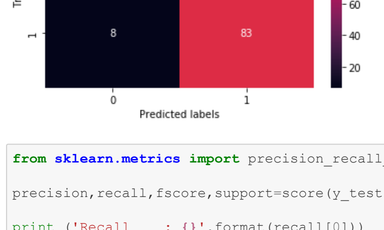
```
In [115]: from sklearn.model_selection import cross_val_score
svc_rbf_grid = SVC(kernel='rbf', gamma = 0.1, C = 0.1)

scores = cross_val_score(svc_rbf_grid, X_train_pca, y_train, cv =10, scoring = 'accuracy')
print("Cross-validation scores: {}".format(scores))

print("Average cross-validation score: {:.2f}".format(scores.mean()))
```

```
Cross-validation scores: [0.94845361 0.96907216 0.89690722 0.95876289 0.96907216 0.91666667
 0.95833333 0.875      0.98958333 0.95833333]
Average cross-validation score: 0.94
```

Confusion Matrix is printed

```
In [116]: pred_rbf = clf2.predict(X_test_pca)
print(metrics.accuracy_score(y_test,pred_rbf))

confusion = confusion_matrix(y_test, pred_rbf)
import seaborn as sns
import matplotlib.pyplot as plt

ax= plt.subplot()
sns.heatmap(confusion, annot=True,fmt='d', ax = ax); #annot=True to annotate cells

# labels, title and ticks
ax.set_xlabel('Predicted labels')
ax.set_ylabel('True labels')

print(classification_report(y_test,pred_rbf))
```

```
0.9380165289256198
              precision    recall  f1-score   support

           0       0.95      0.95      0.95       151
           1       0.92      0.91      0.92        91

    accuracy                           0.94       242
   macro avg       0.93      0.93      0.93       242
weighted avg       0.94      0.94      0.94       242
```




```
In [117]: from sklearn.metrics import precision_recall_fscore_support as score

precision,recall,fscore,support=score(y_test,pred_rbf)

print ('Recall    : {}'.format(recall[0]))
print ('F1Score    : {}'.format(fscore[0]))
```

```
Recall    : 0.9536423841059603
F1Score    : 0.9504950495049505
```

```
In [118]: Classification_Scores.update({'SVC-rbf with PCA':[metrics.accuracy_score(y_test,pred_rbf),recall[0],fs
core[0]]})
```

SVC Poly PCA

SVC Poly is modeled with grid dearch for best param - gamma, C, degree

```
In [119]: param_grid = {'gamma': [0.01,0.1],
                        'C': [0.01, 0.1, 1,10],
                        'degree': [1,2,3,4,5]}

          grid_search_svcp = GridSearchCV(SVC(kernel='poly'), param_grid, cv=5, return_train_score=True)

          grid_search_svcp.fit(X_train_pca, y_train)

          print("Best parameters: {}".format(grid_search_svcp.best_params_))
          print("Best cross-validation score: {:.2f}".format(grid_search_svcp.best_score_))
```

```
Best parameters: {'C': 0.1, 'degree': 1, 'gamma': 0.1}
Best cross-validation score: 0.94
```

Train and Test score of the linear SVC

```
In [120]: clf3 = SVC(kernel='rbf', C=0.1,gamma=0.1,degree=1).fit(X_train_pca, y_train)
          print('Train score on best parameters for LinearSVC - {:.4f}'.format(clf1.score(X_train_pca, y_train
          )))
          print('Test score on best parameters ffor LinearSVC - {:.4f}'.format(clf1.score(X_test_pca,y_test)))
```

```
Train score on best parameters for LinearSVC - 0.9440
Test score on best parameters ffor LinearSVC - 0.9380
```

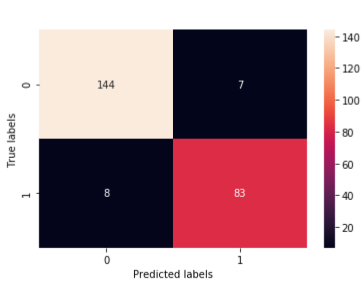
```
In [121]: svc_poly_grid = SVC(kernel='poly',degree = 1, C=0.01, gamma=1)

          scores = cross_val_score(svc_poly_grid, X_train_pca, y_train, cv =5, scoring = 'accuracy')
          print("Cross-validation scores: {}".format(scores))

          print("Average cross-validation score: {:.2f}".format(scores.mean()))
```

```
Cross-validation scores: [0.96373057 0.92227979 0.94300518 0.91709845 0.97409326]
Average cross-validation score: 0.94
```

Confusion Matrix

```
In [122]: # import warnings filter
          from warnings import simplefilter
          # ignore all future warnings
          simplefilter(action='ignore', category=FutureWarning)

          pred_poly = clf3.predict(X_test_pca)
          print(metrics.accuracy_score(y_test,pred_poly))

          confusion = confusion_matrix(y_test, pred_poly)

          import seaborn as sns
          import matplotlib.pyplot as plt

          ax= plt.subplot()
          sns.heatmap(confusion, annot=True,fmt='d', ax = ax); #annot=True to annotate cells

          # labels, title and ticks
          ax.set_xlabel('Predicted labels')
          ax.set_ylabel('True labels')

          print(classification_report(y_test,pred_poly))
```

```
0.9380165289256198
              precision    recall  f1-score   support

           0       0.95      0.95      0.95       151
           1       0.92      0.91      0.92        91

    accuracy                           0.94       242
   macro avg       0.93      0.93      0.93       242
weighted avg       0.94      0.94      0.94       242
```



Recall and F1 score are printed

```
In [123]: from sklearn.metrics import precision_recall_fscore_support as score

          precision,recall,fscore,support=score(y_test,pred_poly)

          print ('Recall    : {}'.format(recall[0]))
          print ('F1Score    : {}'.format(fscore[0]))
```

```
Recall    : 0.9536423841059603
F1Score    : 0.9504950495049505
```

```
In [124]: Classification_Scores.update({'SVC-poly with PCA':[metrics.accuracy_score(y_test,pred_poly),recall[0],
          fscore[0]]})
```

SVC rbf and linear with PCA

SVC RBF is modelled with gridsearch for selecting the best params for C, gamma

```
In [125]: #using Kernel SVM
          from sklearn.svm import SVC
          KernelSVC = SVC(max_iter=10000000)
          kernelSVC_params = {'C':[0.001, 0.01, 0.1, 1],'gamma':[1,0.1,0.001], 'kernel':['rbf','linear']}
```

```
In [126]: # Using Grid search to find the best parameters and fitting the model
          KernelSVC_clf = GridSearchCV(KernelSVC, kernelSVC_params,cv=5)
          KernelSVC_clf.fit(X_train_pca,y_train)
          print('Train score on best parameters for LinearSVC - {:.4f}'.format(clf1.score(X_train_pca, y_train
          )))
          print('Test score on best parameters ffor LinearSVC - {:.4f}'.format(clf1.score(X_test_pca,y_test)))
```

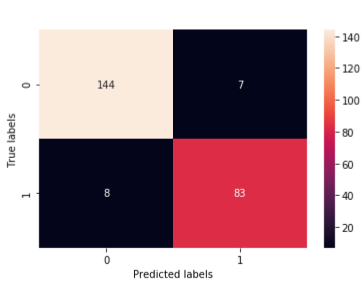
```
Train score on best parameters for LinearSVC - 0.9440
Test score on best parameters ffor LinearSVC - 0.9380
```

```
In [127]: #finding the best paramrter
          KernelSVC_clf.best_params_

Out[127]: {'C': 0.1, 'gamma': 0.1, 'kernel': 'rbf'}
```

CONFUSION MATRIX

```
In [128]: pred_ker_svc = KernelSVC_clf.predict(X_test_pca)
          print(metrics.accuracy_score(y_test,pred_ker_svc))

          confusion = confusion_matrix(y_test, pred_ker_svc)
          import seaborn as sns
          import matplotlib.pyplot as plt

          ax= plt.subplot()
          sns.heatmap(confusion, annot=True,fmt='d', ax = ax); #annot=True to annotate cells

          # labels, title and ticks
          ax.set_xlabel('Predicted labels')
          ax.set_ylabel('True labels')


          print(classification_report(y_test,pred_ker_svc))
```

```
0.9380165289256198
              precision    recall  f1-score   support

           0       0.95      0.95      0.95       151
           1       0.92      0.91      0.92        91

    accuracy                           0.94       242
   macro avg       0.93      0.93      0.93       242
weighted avg       0.94      0.94      0.94       242
```




```
In [129]: from sklearn.metrics import precision_recall_fscore_support as score

          precision,recall,fscore,support=score(y_test,pred_ker_svc)

          print ('Recall    : {}'.format(recall[0]))
          print ('F1Score    : {}'.format(fscore[0]))
```

```
Recall    : 0.9536423841059603
F1Score    : 0.9504950495049505
```

```
In [130]: Classification_Scores.update({'SVC-linear with PCA':[metrics.accuracy_score(y_test,pred_ker_svc),recal
          l[0],fscore[0]]})
```

Decision Tree PCA

Decision tree is modeled after PCA on the dataset with grid search for best param of max_depth and min_sample_leaf

```
In [131]: from sklearn.tree import DecisionTreeClassifier

          param_grid = {'criterion': ['gini','entropy'],
                        'max_depth': [1,2,3,4,5,6,7,8,9,10],
                        'min_samples_leaf': [1,2,3,4,5,6,7,8,9,10]}

          grid_search_dtree = GridSearchCV(DecisionTreeClassifier(random_state=0), param_grid, cv=5, return_trai
          n_score=True)

          grid_search_dtree.fit(X_train_pca, y_train)

          print("Best parameters: {}".format(grid_search_dtree.best_params_))
          print("Best cross-validation score: {:.2f}".format(grid_search_dtree.best_score_))
```

```
Best parameters: {'criterion': 'gini', 'max_depth': 1, 'min_samples_leaf': 1}
Best cross-validation score: 0.93
```

```
In [132]: dtree = DecisionTreeClassifier(max_depth=1,min_samples_leaf=1,criterion='gini')

          dtree.fit(X_train_pca, y_train)
          print("Accuracy on training set: {:.3f}".format(dtree.score(X_train_pca, y_train)))
          print("Accuracy on test set: {:.3f}".format(dtree.score(X_test_pca, y_test)))
```

```
Accuracy on training set: 0.940
Accuracy on test set: 0.934
```

Cross validations score is obtained

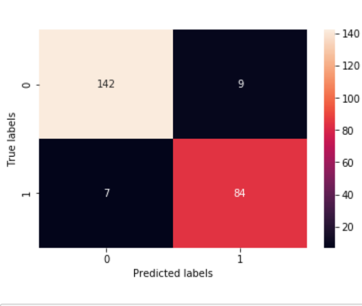
```
In [133]: dtree_cv = DecisionTreeClassifier()
          scores = cross_val_score(dtree_cv, X_train_pca, y_train, cv = 5, scoring = 'accuracy' )
          print("Cross-validation scores: {}".format(scores))

          print("Average cross-validation score: {:.2f}".format(scores.mean()))
```

```
Cross-validation scores: [0.88601036 0.86528497 0.90673575 0.87564767 0.92227979]
Average cross-validation score: 0.89
```

CONFUSION MATRIX

```
In [134]: import sklearn.metrics as metrics
          from sklearn.metrics import confusion_matrix, classification_report
          pred_tree = grid_search_dtree.predict(X_test_pca)
          print(metrics.accuracy_score(y_test,pred_tree))

          confusion = confusion_matrix(y_test, pred_tree)
          import seaborn as sns
          import matplotlib.pyplot as plt

          ax= plt.subplot()
          sns.heatmap(confusion, annot=True,fmt='d', ax = ax); #annot=True to annotate cells

          # labels, title and ticks
          ax.set_xlabel('Predicted labels')
          ax.set_ylabel('True labels')

          print(classification_report(y_test,pred_tree))
```

```
0.9338842975206612
              precision    recall  f1-score   support

           0       0.95      0.94      0.95       151
           1       0.90      0.92      0.91        91

    accuracy                           0.93       242
   macro avg       0.93      0.93      0.93       242
weighted avg       0.93      0.93      0.93       242
```




```
In [135]: from sklearn.metrics import precision_recall_fscore_support as score

          precision,recall,fscore,support=score(y_test,pred_tree)

          print ('Recall    : {}'.format(recall[0]))
          print ('F1Score    : {}'.format(fscore[0]))
```

```
Recall    : 0.9403973509933775
F1Score    : 0.9466666666666667
```

```
In [136]: Classification_Scores.update({'Decision Tree with PCA':[metrics.accuracy_score(y_test,pred_tree),recal
          l[0],fscore[0]]})
```

COMPARISON OF ALL MODELS

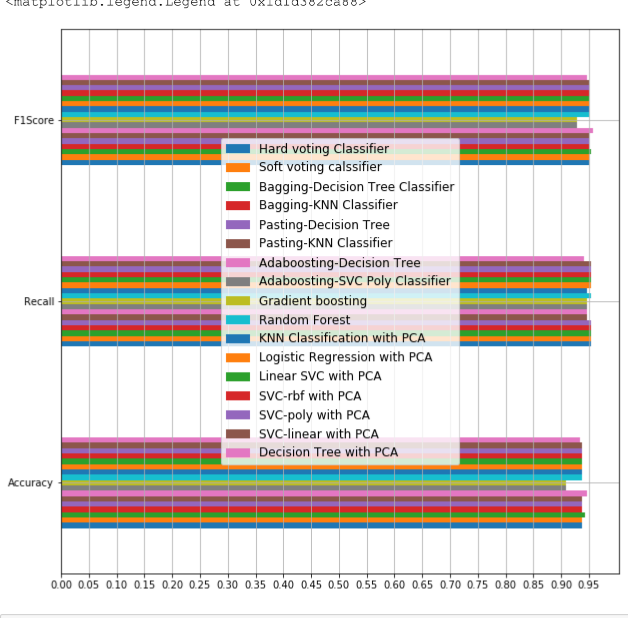
```
In [137]: x1=Classification_Scores.keys()
          df1=pd.DataFrame(Classification_Scores,index=['Accuracy','Recall','F1Score'])
          df1
```

Out[137]:

	Hard voting Classifier	Soft voting calssifier	Bagging-Decision Tree Classifier	Bagging-KNN Classifier	Pasting-Decision Tree	Pasting-KNN Classifier	Adaboosting-Decision Tree	Adaboosting-SVC Poly Classifier	Gradient boosting	Random Forest	KNN Classification with PCA
Accuracy	0.938017	0.938017	0.942149	0.938017	0.938017	0.938017	0.946281	0.909091	0.909091	0.938017	0.938017
Recall	0.953642	0.953642	0.953642	0.953642	0.953642	0.947020	0.947020	0.947020	0.947020	0.953642	0.947020
F1Score	0.950495	0.950495	0.953642	0.950495	0.950495	0.950166	0.956522	0.928571	0.928571	0.950495	0.950166

The accuracy, recall and F1 score for the models are printed before and after PCA

```
In [138]: pd.DataFrame(df1).plot(kind='barh',figsize=(10,10))
          plt.grid(which='both')
          plt.xticks(np.arange(0,1,step=0.05))
          plt.legend(loc='center',prop={'size':12})

Out[138]: <matplotlib.legend.Legend at 0x1d1d382ca88>
```



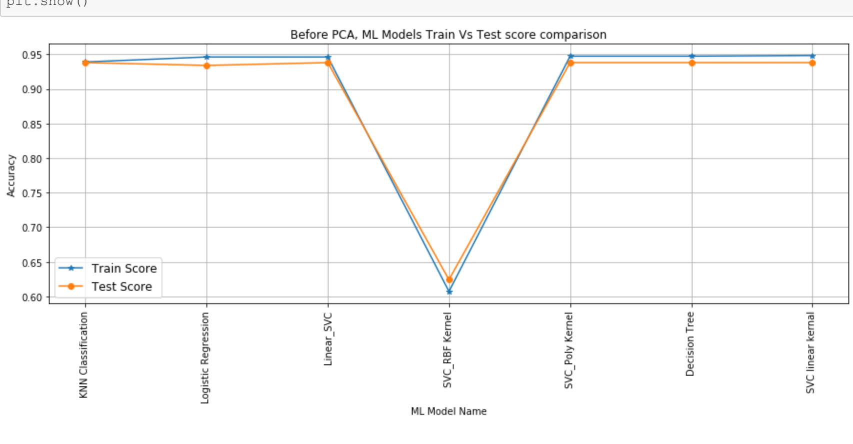

```
In [139]: import pandas as pd
          project_1=pd.DataFrame({"classifier":["KNN Classification without PCA","KNN Classification with PCA",
          "Logistic Regression without PCA","Logistic Regression with PCA","Linear_SVC without PCA","Linear_SVC
           with PCA","SVC_RBF Kernel without PCA","SVC_RBF Kernel with PCA","SVC_Poly Kernel without PCA","SVC_P
          oly Kernel with PCA","Decision Tree without PCA","Decision Tree with PCA","SVC linear kernal without P
          CA ","SVC linear kernal with PCA"],
                                  "Train Score":[0.9389,0.9461,0.9461,0.9420,0.9461,0.9440,0.6070,0.9440,0.9472,
          0.9440,0.9472, 0.9440,0.9482,0.9400],
                                  "Test score":[0.9380,0.9380,0.9339,0.9380,0.9380, 0.9380,0.6240,0.9380,0.9380,
          0.9380,0.9380,0.9380,0.9380,0.9340],
                                  "Accuracy":[93.80,93.80,93.38,93.80,93.80,93.80,62.39,93.80, 93.80,93.80,62.39
          ,93.80,93.80,93.38 ]})
          project_1
```

Out[139]:

	classifier	Train Score	Test score	Accuracy
0	KNN Classification without PCA	0.9389	0.9380	93.80
1	KNN Classification with PCA	0.9461	0.9380	93.80
2	Logistic Regression without PCA	0.9461	0.9339	93.38
3	Logistic Regression with PCA	0.9420	0.9380	93.80
4	Linear_SVC without PCA	0.9461	0.9380	93.80
5	Linear_SVC with PCA	0.9440	0.9380	93.80
6	SVC_RBF Kernel without PCA	0.6070	0.6240	62.39
7	SVC_RBF Kernel with PCA	0.9440	0.9380	93.80
8	SVC_Poly Kernel without PCA	0.9472	0.9380	93.80
9	SVC_Poly Kernel with PCA	0.9440	0.9380	93.80
10	Decision Tree without PCA	0.9472	0.9380	62.39
11	Decision Tree with PCA	0.9440	0.9380	93.80
12	SVC linear kernal without PCA	0.9482	0.9380	93.80
13	SVC linear kernal with PCA	0.9400	0.9340	93.38

BEFORE PCA

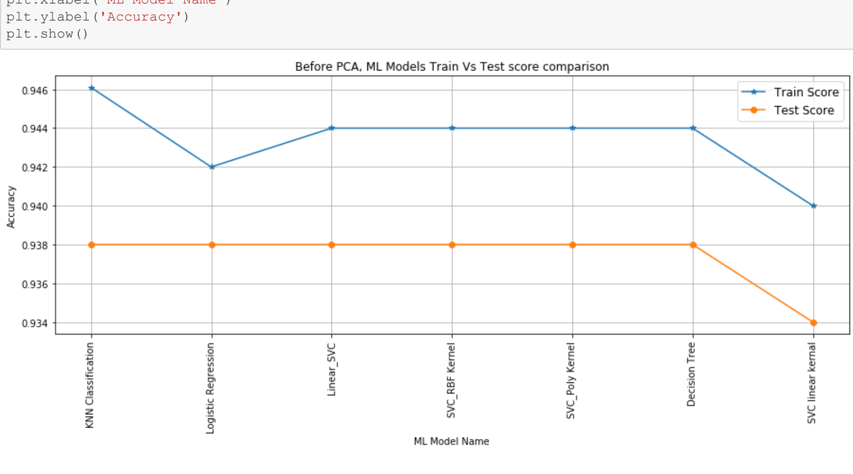
```
In [140]: import matplotlib.pyplot as plt
          btrainscore=[0.9389,0.9461,0.9461,0.6070,0.9472,0.9472, 0.9482]
          btestscore =[0.9380,0.9339,0.9380,0.6240,0.9380,0.9380,0.9380]
          Models=["KNN Classification","Logistic Regression","Linear_SVC","SVC_RBF Kernel","SVC_Poly Kernel","De
          cision Tree","SVC linear kernal"]

          plt.figure(figsize=(15,5))
          plt.plot(Models,btrainscore,marker='*',label='Train Score')
          plt.plot(Models,btestscore,marker='o',label='Test Score')
          plt.legend(prop={'size': 12})
          plt.grid()
          plt.xticks(rotation='vertical')
          plt.title('Before PCA, ML Models Train Vs Test score comparison')
          plt.xlabel('ML Model Name')
          plt.ylabel('Accuracy')
          plt.show()
```



Before PCA, we find that SVM Kernel poly was the better model with low test and train score difference.

AFTER PCA

```
In [141]: import matplotlib.pyplot as plt
          btrainscore=[0.9461,0.9420,0.9440,0.9440,0.9440, 0.9440,0.9400]

          btestscore =[0.9380,0.9380, 0.9380,0.9380,0.9380,0.9380,0.9340]
          Models=["KNN Classification","Logistic Regression","Linear_SVC","SVC_RBF Kernel","SVC_Poly Kernel","De
          cision Tree","SVC linear kernal"]

          plt.figure(figsize=(15,5))
          plt.plot(Models,btrainscore,marker='*',label='Train Score')
          plt.plot(Models,btestscore,marker='o',label='Test Score')
          plt.legend(prop={'size': 12})
          plt.grid()
          plt.xticks(rotation='vertical')
          plt.title('Before PCA, ML Models Train Vs Test score comparison')
          plt.xlabel('ML Model Name')
          plt.ylabel('Accuracy')
          plt.show()
```



After PCA was performed, we find that KNN model was better with a higher train and lower difference with test and train score

OverAll, we find that after use of PCA on the dataset, KNN and SVC RBF have performed better than before. This is owed to the dimension reduction in the dataset.

For our dataset, we see that KNN has performed better as its accuracy and test and train core difference is less after PCA.

BEST MODEL OVERALL: KNN Classifier with Train - 0.946 and test= 0.9380 and accuracy 93.80

Deep Learning Tasks

Neural Networks

```
In [142]: import tensorflow as tf
          from tensorflow.keras.models import Sequential
          from tensorflow.keras.layers import Dense
          import numpy

          # fix random seed for reproducibility
          numpy.random.seed(10)
```

```
In [143]: import tensorflow as tf
```

```
In [144]: model = Sequential()
          model.add(Dense(12, input_dim=43, activation='relu'))
          model.add(Dense(8, activation='relu'))
          model.add(Dense(1, activation='sigmoid'))
```

```
In [145]: model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
```

```
In [146]: X_train=np.asarray(X_train)
          y_train = np.asarray(y_train)
          X_test=np.asarray(X_test)
          y_test = np.asarray(y_test)
```

In [147]:
```
from tensorflow import keras
neural_model=model.fit(X_train, y_train, epochs=150,batch_size=10)
```

```
Epoch 1/150
97/97 [==============================] - 0s 1ms/step - loss: 0.6643 - accuracy: 0.4777
Epoch 2/150
97/97 [==============================] - 0s 1ms/step - loss: 0.5585 - accuracy: 0.8176
Epoch 3/150
97/97 [==============================] - 0s 1ms/step - loss: 0.4940 - accuracy: 0.9244
Epoch 4/150
97/97 [==============================] - 0s 1ms/step - loss: 0.4598 - accuracy: 0.9358
Epoch 5/150
97/97 [==============================] - 0s 1ms/step - loss: 0.4340 - accuracy: 0.9430
Epoch 6/150
97/97 [==============================] - 0s 1ms/step - loss: 0.4135 - accuracy: 0.9451
Epoch 7/150
97/97 [==============================] - 0s 1ms/step - loss: 0.3951 - accuracy: 0.9451
Epoch 8/150
97/97 [==============================] - 0s 1ms/step - loss: 0.3774 - accuracy: 0.9451
Epoch 9/150
97/97 [==============================] - 0s 1ms/step - loss: 0.3626 - accuracy: 0.9451
Epoch 10/150
97/97 [==============================] - 0s 1ms/step - loss: 0.3490 - accuracy: 0.9451
Epoch 11/150
97/97 [==============================] - 0s 1ms/step - loss: 0.3347 - accuracy: 0.9451
Epoch 12/150
97/97 [==============================] - 0s 1ms/step - loss: 0.3231 - accuracy: 0.9451
Epoch 13/150
97/97 [==============================] - 0s 1ms/step - loss: 0.3125 - accuracy: 0.9451
Epoch 14/150
97/97 [==============================] - 0s 1ms/step - loss: 0.3008 - accuracy: 0.9451
Epoch 15/150
97/97 [==============================] - 0s 1ms/step - loss: 0.2930 - accuracy: 0.9451
Epoch 16/150
97/97 [==============================] - 0s 1ms/step - loss: 0.2839 - accuracy: 0.9461
Epoch 17/150
97/97 [==============================] - 0s 1ms/step - loss: 0.2770 - accuracy: 0.9451
Epoch 18/150
97/97 [==============================] - 0s 1ms/step - loss: 0.2709 - accuracy: 0.9461
Epoch 19/150
97/97 [==============================] - 0s 1ms/step - loss: 0.2622 - accuracy: 0.9451
Epoch 20/150
97/97 [==============================] - 0s 1ms/step - loss: 0.2552 - accuracy: 0.9451
Epoch 21/150
97/97 [==============================] - 0s 1ms/step - loss: 0.2497 - accuracy: 0.9451
Epoch 22/150
97/97 [==============================] - 0s 1ms/step - loss: 0.2453 - accuracy: 0.9451
Epoch 23/150
97/97 [==============================] - 0s 1ms/step - loss: 0.2390 - accuracy: 0.9451
Epoch 24/150
97/97 [==============================] - 0s 1ms/step - loss: 0.2331 - accuracy: 0.9461
Epoch 25/150
97/97 [==============================] - 0s 1ms/step - loss: 0.2291 - accuracy: 0.9461
Epoch 26/150
97/97 [==============================] - 0s 1ms/step - loss: 0.2237 - accuracy: 0.9472
Epoch 27/150
97/97 [==============================] - 0s 1ms/step - loss: 0.2174 - accuracy: 0.9472
Epoch 28/150
97/97 [==============================] - 0s 1ms/step - loss: 0.2136 - accuracy: 0.9472
Epoch 29/150
97/97 [==============================] - 0s 1ms/step - loss: 0.2113 - accuracy: 0.9472
Epoch 30/150
97/97 [==============================] - 0s 2ms/step - loss: 0.2061 - accuracy: 0.9482
Epoch 31/150
97/97 [==============================] - 0s 1ms/step - loss: 0.2025 - accuracy: 0.9482
Epoch 32/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1986 - accuracy: 0.9482
Epoch 33/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1958 - accuracy: 0.9492
Epoch 34/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1924 - accuracy: 0.9482
Epoch 35/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1889 - accuracy: 0.9534
Epoch 36/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1857 - accuracy: 0.9523
Epoch 37/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1834 - accuracy: 0.9523
Epoch 38/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1810 - accuracy: 0.9523
Epoch 39/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1777 - accuracy: 0.9534
Epoch 40/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1763 - accuracy: 0.9554
Epoch 41/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1724 - accuracy: 0.9565
Epoch 42/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1720 - accuracy: 0.9565
Epoch 43/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1698 - accuracy: 0.9544
Epoch 44/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1681 - accuracy: 0.9554
Epoch 45/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1653 - accuracy: 0.9554
Epoch 46/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1640 - accuracy: 0.9544
Epoch 47/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1620 - accuracy: 0.9565
Epoch 48/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1624 - accuracy: 0.9554
Epoch 49/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1579 - accuracy: 0.9575
Epoch 50/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1577 - accuracy: 0.9596
Epoch 51/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1564 - accuracy: 0.9575
Epoch 52/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1546 - accuracy: 0.9575
Epoch 53/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1525 - accuracy: 0.9565
Epoch 54/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1504 - accuracy: 0.9606
Epoch 55/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1512 - accuracy: 0.9585
Epoch 56/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1497 - accuracy: 0.9565
Epoch 57/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1483 - accuracy: 0.9575
Epoch 58/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1493 - accuracy: 0.9585
Epoch 59/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1459 - accuracy: 0.9596
Epoch 60/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1453 - accuracy: 0.9554
Epoch 61/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1444 - accuracy: 0.9585
Epoch 62/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1416 - accuracy: 0.9554
Epoch 63/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1423 - accuracy: 0.9585
Epoch 64/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1411 - accuracy: 0.9585
Epoch 65/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1408 - accuracy: 0.9575
Epoch 66/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1382 - accuracy: 0.9585
Epoch 67/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1392 - accuracy: 0.9596
Epoch 68/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1402 - accuracy: 0.9596
Epoch 69/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1364 - accuracy: 0.9585
Epoch 70/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1371 - accuracy: 0.9617
Epoch 71/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1370 - accuracy: 0.9585
Epoch 72/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1349 - accuracy: 0.9617
Epoch 73/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1346 - accuracy: 0.9585
Epoch 74/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1335 - accuracy: 0.9606
Epoch 75/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1340 - accuracy: 0.9596
Epoch 76/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1316 - accuracy: 0.9617
Epoch 77/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1304 - accuracy: 0.9606
Epoch 78/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1317 - accuracy: 0.9606
Epoch 79/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1306 - accuracy: 0.9575
Epoch 80/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1303 - accuracy: 0.9606
Epoch 81/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1303 - accuracy: 0.9596
Epoch 82/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1280 - accuracy: 0.9596
Epoch 83/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1273 - accuracy: 0.9617
Epoch 84/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1266 - accuracy: 0.9596
Epoch 85/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1257 - accuracy: 0.9606
Epoch 86/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1267 - accuracy: 0.9606
Epoch 87/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1257 - accuracy: 0.9617
Epoch 88/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1236 - accuracy: 0.9617
Epoch 89/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1258 - accuracy: 0.9617
Epoch 90/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1240 - accuracy: 0.9627
Epoch 91/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1238 - accuracy: 0.9606
Epoch 92/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1241 - accuracy: 0.9627
Epoch 93/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1230 - accuracy: 0.9606
Epoch 94/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1213 - accuracy: 0.9617
Epoch 95/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1231 - accuracy: 0.9627
Epoch 96/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1200 - accuracy: 0.9627
Epoch 97/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1200 - accuracy: 0.9627
Epoch 98/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1212 - accuracy: 0.9627
Epoch 99/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1198 - accuracy: 0.9575
Epoch 100/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1188 - accuracy: 0.9596
Epoch 101/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1200 - accuracy: 0.9627
Epoch 102/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1191 - accuracy: 0.9617
Epoch 103/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1184 - accuracy: 0.9637
Epoch 104/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1169 - accuracy: 0.9627
Epoch 105/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1166 - accuracy: 0.9596
Epoch 106/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1155 - accuracy: 0.9627
Epoch 107/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1157 - accuracy: 0.9606
Epoch 108/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1154 - accuracy: 0.9606
Epoch 109/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1153 - accuracy: 0.9617
Epoch 110/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1160 - accuracy: 0.9637
Epoch 111/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1134 - accuracy: 0.9637
Epoch 112/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1143 - accuracy: 0.9627
Epoch 113/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1121 - accuracy: 0.9617
Epoch 114/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1119 - accuracy: 0.9627
Epoch 115/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1135 - accuracy: 0.9627
Epoch 116/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1109 - accuracy: 0.9648
Epoch 117/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1137 - accuracy: 0.9606
Epoch 118/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1121 - accuracy: 0.9637
Epoch 119/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1098 - accuracy: 0.9637
Epoch 120/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1103 - accuracy: 0.9648
Epoch 121/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1093 - accuracy: 0.9648
Epoch 122/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1108 - accuracy: 0.9648
Epoch 123/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1088 - accuracy: 0.9637
Epoch 124/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1084 - accuracy: 0.9658
Epoch 125/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1080 - accuracy: 0.9637
Epoch 126/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1087 - accuracy: 0.9648
Epoch 127/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1067 - accuracy: 0.9668
Epoch 128/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1065 - accuracy: 0.9679
Epoch 129/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1071 - accuracy: 0.9648
Epoch 130/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1057 - accuracy: 0.9658
Epoch 131/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1044 - accuracy: 0.9679
Epoch 132/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1057 - accuracy: 0.9648
Epoch 133/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1049 - accuracy: 0.9668
Epoch 134/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1038 - accuracy: 0.9668
Epoch 135/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1041 - accuracy: 0.9648
Epoch 136/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1036 - accuracy: 0.9658
Epoch 137/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1026 - accuracy: 0.9710
Epoch 138/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1023 - accuracy: 0.9648
Epoch 139/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1014 - accuracy: 0.9689
Epoch 140/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1050 - accuracy: 0.9658
Epoch 141/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1009 - accuracy: 0.9668
Epoch 142/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1020 - accuracy: 0.9658
Epoch 143/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1001 - accuracy: 0.9668
Epoch 144/150
97/97 [==============================] - 0s 1ms/step - loss: 0.0989 - accuracy: 0.9699
Epoch 145/150
97/97 [==============================] - 0s 1ms/step - loss: 0.1001 - accuracy: 0.9679
Epoch 146/150
97/97 [==============================] - 0s 1ms/step - loss: 0.0999 - accuracy: 0.9668
Epoch 147/150
97/97 [==============================] - 0s 1ms/step - loss: 0.0989 - accuracy: 0.9679
Epoch 148/150
97/97 [==============================] - 0s 1ms/step - loss: 0.0994 - accuracy: 0.9658
Epoch 149/150
97/97 [==============================] - 0s 1ms/step - loss: 0.0973 - accuracy: 0.9699
Epoch 150/150
97/97 [==============================] - 0s 1ms/step - loss: 0.0987 - accuracy: 0.9689
```

evaluate the model

In [148]:
```
scores = model.evaluate(X_test, y_test)
print("\n%s: %.2f%%" % (model.metrics_names[1], scores[1]*100))
```

```
8/8 [==============================] - 0s 876us/step - loss: 0.3090 - accuracy: 0.9298

accuracy: 92.98%
```

Single Layer Perceptron

In [149]:
```
def create_model():
    #step 1: build model
    model = Sequential()
    #input layer
    model.add(Dense(12, input_dim = 43, activation = 'relu'))
    #hidden layers
    #output layer
    model.add(Dense(1, activation = 'sigmoid'))
    #step 2: make computational graph - compile
    model.compile(loss= 'binary_crossentropy' , optimizer = 'adam',metrics = ['accuracy'] )
    return model
```

In [150]:
```
seed = 10
np.random.seed(10)
```

In [151]:
```
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import Sequential
from tensorflow.keras.layers import Dense
from keras.wrappers.scikit_learn import KerasClassifier
from sklearn.model_selection import GridSearchCV

model = KerasClassifier(build_fn = create_model, verbose = 0)

param_grid = {'batch_size':[10,30,40] , 'epochs':[50, 100]}
grid_search = GridSearchCV(estimator= model, param_grid = param_grid, cv = 5)
```

In [152]:
```
grid_search_result = grid_search.fit(X_train, y_train)
```

In [153]:
```
print("Best parameters: {}".format(grid_search.best_params_))
print("Best cross-validation score: {:.2f}".format(grid_search.best_score_))
```

```
Best parameters: {'batch_size': 40, 'epochs': 50}
Best cross-validation score: 0.95
```

In [154]:
```
#step 1: build model
model1 = Sequential()
#input layer
model1.add(Dense(12, input_dim = 43, activation = 'relu'))
#hidden layers
#output layer
model1.add(Dense(1, activation = 'sigmoid'))
#step 2: make computational graph - compile
model1.compile(loss= 'binary_crossentropy' , optimizer = 'adam',metrics = ['accuracy'] )
```

In [155]:
```
# Fit the model
model1.fit(X_train, y_train, epochs=100, batch_size=30)
```

```
Epoch 1/100
33/33 [==============================] - 0s 997us/step - loss: 0.7132 - accuracy: 0.5824
Epoch 2/100
33/33 [==============================] - 0s 1ms/step - loss: 0.6381 - accuracy: 0.6456
Epoch 3/100
33/33 [==============================] - 0s 1ms/step - loss: 0.5715 - accuracy: 0.7254
Epoch 4/100
33/33 [==============================] - 0s 1ms/step - loss: 0.5078 - accuracy: 0.8093
Epoch 5/100
33/33 [==============================] - 0s 1ms/step - loss: 0.4451 - accuracy: 0.8570
Epoch 6/100
33/33 [==============================] - 0s 1ms/step - loss: 0.3805 - accuracy: 0.8902
Epoch 7/100
33/33 [==============================] - 0s 1ms/step - loss: 0.3227 - accuracy: 0.9130
Epoch 8/100
33/33 [==============================] - 0s 1ms/step - loss: 0.2798 - accuracy: 0.9233
Epoch 9/100
33/33 [==============================] - 0s 1ms/step - loss: 0.2519 - accuracy: 0.9275
Epoch 10/100
33/33 [==============================] - 0s 1ms/step - loss: 0.2322 - accuracy: 0.9306
Epoch 11/100
33/33 [==============================] - 0s 1ms/step - loss: 0.2194 - accuracy: 0.9358
Epoch 12/100
33/33 [==============================] - 0s 1ms/step - loss: 0.2101 - accuracy: 0.9409
Epoch 13/100
33/33 [==============================] - 0s 1ms/step - loss: 0.2016 - accuracy: 0.9451
Epoch 14/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1964 - accuracy: 0.9451
Epoch 15/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1934 - accuracy: 0.9440
Epoch 16/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1895 - accuracy: 0.9451
Epoch 17/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1867 - accuracy: 0.9461
Epoch 18/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1842 - accuracy: 0.9451
Epoch 19/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1827 - accuracy: 0.9451
Epoch 20/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1816 - accuracy: 0.9461
Epoch 21/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1794 - accuracy: 0.9451
Epoch 22/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1789 - accuracy: 0.9451
Epoch 23/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1768 - accuracy: 0.9440
Epoch 24/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1765 - accuracy: 0.9451
Epoch 25/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1752 - accuracy: 0.9461
Epoch 26/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1738 - accuracy: 0.9472
Epoch 27/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1741 - accuracy: 0.9482
Epoch 28/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1720 - accuracy: 0.9472
Epoch 29/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1719 - accuracy: 0.9461
Epoch 30/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1702 - accuracy: 0.9482
Epoch 31/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1701 - accuracy: 0.9482
Epoch 32/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1694 - accuracy: 0.9472
Epoch 33/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1680 - accuracy: 0.9482
Epoch 34/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1669 - accuracy: 0.9482
Epoch 35/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1659 - accuracy: 0.9482
Epoch 36/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1652 - accuracy: 0.9482
Epoch 37/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1648 - accuracy: 0.9482
Epoch 38/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1640 - accuracy: 0.9482
Epoch 39/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1634 - accuracy: 0.9482
Epoch 40/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1627 - accuracy: 0.9482
Epoch 41/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1619 - accuracy: 0.9482
Epoch 42/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1615 - accuracy: 0.9482
Epoch 43/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1614 - accuracy: 0.9482
Epoch 44/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1602 - accuracy: 0.9492
Epoch 45/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1600 - accuracy: 0.9482
Epoch 46/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1591 - accuracy: 0.9482
Epoch 47/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1583 - accuracy: 0.9492
Epoch 48/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1578 - accuracy: 0.9492
Epoch 49/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1583 - accuracy: 0.9492
Epoch 50/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1577 - accuracy: 0.9482
Epoch 51/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1567 - accuracy: 0.9482
Epoch 52/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1563 - accuracy: 0.9492
Epoch 53/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1563 - accuracy: 0.9482
Epoch 54/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1550 - accuracy: 0.9472
Epoch 55/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1548 - accuracy: 0.9492
Epoch 56/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1548 - accuracy: 0.9492
Epoch 57/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1539 - accuracy: 0.9492
Epoch 58/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1540 - accuracy: 0.9492
Epoch 59/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1533 - accuracy: 0.9482
Epoch 60/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1530 - accuracy: 0.9492
Epoch 61/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1523 - accuracy: 0.9492
Epoch 62/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1521 - accuracy: 0.9492
Epoch 63/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1517 - accuracy: 0.9492
Epoch 64/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1514 - accuracy: 0.9492
Epoch 65/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1511 - accuracy: 0.9482
Epoch 66/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1505 - accuracy: 0.9492
Epoch 67/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1499 - accuracy: 0.9492
Epoch 68/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1497 - accuracy: 0.9492
Epoch 69/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1496 - accuracy: 0.9523
Epoch 70/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1496 - accuracy: 0.9523
Epoch 71/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1485 - accuracy: 0.9503
Epoch 72/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1487 - accuracy: 0.9492
Epoch 73/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1481 - accuracy: 0.9503
Epoch 74/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1483 - accuracy: 0.9523
Epoch 75/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1474 - accuracy: 0.9523
Epoch 76/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1473 - accuracy: 0.9513
Epoch 77/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1473 - accuracy: 0.9513
Epoch 78/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1466 - accuracy: 0.9503
Epoch 79/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1462 - accuracy: 0.9513
Epoch 80/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1461 - accuracy: 0.9523
Epoch 81/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1457 - accuracy: 0.9534
Epoch 82/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1454 - accuracy: 0.9534
Epoch 83/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1457 - accuracy: 0.9523
Epoch 84/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1451 - accuracy: 0.9534
Epoch 85/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1453 - accuracy: 0.9513
Epoch 86/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1444 - accuracy: 0.9534
Epoch 87/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1446 - accuracy: 0.9534
Epoch 88/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1440 - accuracy: 0.9534
Epoch 89/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1434 - accuracy: 0.9534
Epoch 90/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1432 - accuracy: 0.9534
Epoch 91/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1427 - accuracy: 0.9544
Epoch 92/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1427 - accuracy: 0.9534
Epoch 93/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1424 - accuracy: 0.9544
Epoch 94/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1429 - accuracy: 0.9513
Epoch 95/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1421 - accuracy: 0.9544
Epoch 96/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1420 - accuracy: 0.9523
Epoch 97/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1417 - accuracy: 0.9544
Epoch 98/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1424 - accuracy: 0.9534
Epoch 99/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1412 - accuracy: 0.9534
Epoch 100/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1406 - accuracy: 0.9544
```

Out[155]:
```
<tensorflow.python.keras.callbacks.History at 0x1d1fc094888>
```

Evaluation Metrics

In [156]:
```
model1.evaluate(X_train, y_train)
```

```
 1/31 [..............................] - ETA: 0s - loss: 0.1076 - accuracy: 0.9688WARNING:tensorflow:
Callbacks method `on_test_batch_end` is slow compared to the batch time (batch time: 0.0000s vs `on_t
est_batch_end` time: 0.0010s). Check your callbacks.
31/31 [==============================] - 0s 837us/step - loss: 0.1397 - accuracy: 0.9544
```

Out[156]:
```
[0.13971954584121704, 0.9544041156768799]
```

In [157]:
```
model1.evaluate(X_test, y_test)
```

```
8/8 [==============================] - 0s 997us/step - loss: 0.2075 - accuracy: 0.9380
```

Out[157]:
```
[0.2074800431728363, 0.9380165338516235]
```

Prediction Score

In [158]:
```
import tensorflow as tf
import logging
tf.get_logger().setLevel(logging.ERROR)
train_pred=model1.predict_classes(X_train)
pred=model1.predict_classes(X_test)
```

In [159]:
```
from sklearn.metrics import precision_score
print("train",precision_score(y_train, train_pred))
print("test",precision_score(y_test,pred))
```

```
train 0.9257425742574258
test 0.9042553191489362
```

2.Multi-Level Perceptron

In [160]:
```
def create_model1():
    #step 1: build model
    model1 = Sequential()
    #input layer
    model1.add(Dense(30, input_dim = 76, activation = 'relu'))
    #hidden layers
    model1.add(Dense(20, activation = 'relu'))
    model1.add(Dense(10, activation = 'relu'))
    #output layer
    model1.add(Dense(1, activation = 'sigmoid'))

    #step 2: make computational graph - compile
    model1.compile(loss= 'binary_crossentropy' , optimizer = 'adam',metrics = ['accuracy'] )
    return model1
```

In [161]:
```
from sklearn.model_selection import GridSearchCV

model = KerasClassifier(build_fn = create_model, verbose = 0)

param_grid = {'batch_size':[10,30,40] , 'epochs':[50, 100]}
grid_search = GridSearchCV(estimator= model, param_grid = param_grid, cv = 5)
```

In [162]:
```
grid_search_result = grid_search.fit(X_train, y_train)
```

In [163]:
```
print("Best parameters: {}".format(grid_search.best_params_))
print("Best cross-validation score: {:.2f}".format(grid_search.best_score_))
```

```
Best parameters: {'batch_size': 40, 'epochs': 50}
Best cross-validation score: 0.95
```

In [164]:
```
#step 1: build model
model1 = Sequential()
#input layer
model1.add(Dense(30, input_dim = 43, activation = 'relu'))
#hidden layers
model1.add(Dense(20, activation = 'relu'))
model1.add(Dense(10, activation = 'relu'))
#output layer
model1.add(Dense(1, activation = 'sigmoid'))

#step 2: make computational graph - compile
model1.compile(loss= 'binary_crossentropy' , optimizer = 'adam',metrics = ['accuracy'] )
```

In [165]:
```
# Fit the model
model1.fit(X_train, y_train, epochs=100, batch_size=30)
```

```
Epoch 1/100
33/33 [==============================] - 0s 1ms/step - loss: 0.6818 - accuracy: 0.5399
Epoch 2/100
33/33 [==============================] - 0s 1ms/step - loss: 0.5995 - accuracy: 0.6508
Epoch 3/100
33/33 [==============================] - 0s 1ms/step - loss: 0.4570 - accuracy: 0.8902
Epoch 4/100
33/33 [==============================] - 0s 1ms/step - loss: 0.2822 - accuracy: 0.9347
Epoch 5/100
33/33 [==============================] - 0s 1ms/step - loss: 0.2148 - accuracy: 0.9430
Epoch 6/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1988 - accuracy: 0.9430
Epoch 7/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1877 - accuracy: 0.9451
Epoch 8/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1799 - accuracy: 0.9461
Epoch 9/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1761 - accuracy: 0.9451
Epoch 10/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1717 - accuracy: 0.9451
Epoch 11/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1709 - accuracy: 0.9472
Epoch 12/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1644 - accuracy: 0.9513
Epoch 13/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1617 - accuracy: 0.9482
Epoch 14/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1589 - accuracy: 0.9513
Epoch 15/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1569 - accuracy: 0.9554
Epoch 16/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1550 - accuracy: 0.9523
Epoch 17/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1528 - accuracy: 0.9534
Epoch 18/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1488 - accuracy: 0.9575
Epoch 19/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1475 - accuracy: 0.9534
Epoch 20/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1452 - accuracy: 0.9534
Epoch 21/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1442 - accuracy: 0.9565
Epoch 22/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1414 - accuracy: 0.9565
Epoch 23/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1398 - accuracy: 0.9575
Epoch 24/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1381 - accuracy: 0.9554
Epoch 25/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1352 - accuracy: 0.9575
Epoch 26/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1339 - accuracy: 0.9596
Epoch 27/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1323 - accuracy: 0.9596
Epoch 28/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1307 - accuracy: 0.9565
Epoch 29/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1294 - accuracy: 0.9596
Epoch 30/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1277 - accuracy: 0.9585
Epoch 31/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1275 - accuracy: 0.9596
Epoch 32/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1232 - accuracy: 0.9596
Epoch 33/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1220 - accuracy: 0.9596
Epoch 34/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1209 - accuracy: 0.9585
Epoch 35/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1218 - accuracy: 0.9617
Epoch 36/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1176 - accuracy: 0.9606
Epoch 37/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1159 - accuracy: 0.9617
Epoch 38/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1148 - accuracy: 0.9617
Epoch 39/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1153 - accuracy: 0.9627
Epoch 40/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1179 - accuracy: 0.9585
Epoch 41/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1118 - accuracy: 0.9606
Epoch 42/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1089 - accuracy: 0.9606
Epoch 43/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1126 - accuracy: 0.9617
Epoch 44/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1098 - accuracy: 0.9606
Epoch 45/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1055 - accuracy: 0.9627
Epoch 46/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1055 - accuracy: 0.9606
Epoch 47/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1060 - accuracy: 0.9606
Epoch 48/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1050 - accuracy: 0.9627
Epoch 49/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1084 - accuracy: 0.9606
Epoch 50/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1032 - accuracy: 0.9617
Epoch 51/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1009 - accuracy: 0.9648
Epoch 52/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1054 - accuracy: 0.9617
Epoch 53/100
33/33 [==============================] - 0s 1ms/step - loss: 0.1000 - accuracy: 0.9637
Epoch 54/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0967 - accuracy: 0.9658
Epoch 55/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0962 - accuracy: 0.9648
Epoch 56/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0966 - accuracy: 0.9637
Epoch 57/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0944 - accuracy: 0.9637
Epoch 58/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0943 - accuracy: 0.9648
Epoch 59/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0916 - accuracy: 0.9668
Epoch 60/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0935 - accuracy: 0.9668
Epoch 61/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0911 - accuracy: 0.9648
Epoch 62/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0900 - accuracy: 0.9668
Epoch 63/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0896 - accuracy: 0.9658
Epoch 64/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0955 - accuracy: 0.9648
Epoch 65/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0867 - accuracy: 0.9648
Epoch 66/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0866 - accuracy: 0.9658
Epoch 67/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0900 - accuracy: 0.9637
Epoch 68/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0872 - accuracy: 0.9637
Epoch 69/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0852 - accuracy: 0.9668
Epoch 70/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0885 - accuracy: 0.9658
Epoch 71/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0835 - accuracy: 0.9658
Epoch 72/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0859 - accuracy: 0.9637
Epoch 73/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0825 - accuracy: 0.9648
Epoch 74/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0815 - accuracy: 0.9658
Epoch 75/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0815 - accuracy: 0.9658
Epoch 76/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0821 - accuracy: 0.9658
Epoch 77/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0791 - accuracy: 0.9689
Epoch 78/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0815 - accuracy: 0.9658
Epoch 79/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0794 - accuracy: 0.9658
Epoch 80/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0802 - accuracy: 0.9689
Epoch 81/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0793 - accuracy: 0.9658
Epoch 82/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0780 - accuracy: 0.9699
Epoch 83/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0782 - accuracy: 0.9689
Epoch 84/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0750 - accuracy: 0.9689
Epoch 85/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0793 - accuracy: 0.9648
Epoch 86/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0743 - accuracy: 0.9658
Epoch 87/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0782 - accuracy: 0.9668
Epoch 88/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0765 - accuracy: 0.9668
Epoch 89/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0763 - accuracy: 0.9689
Epoch 90/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0831 - accuracy: 0.9699
Epoch 91/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0737 - accuracy: 0.9679
Epoch 92/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0778 - accuracy: 0.9668
Epoch 93/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0726 - accuracy: 0.9699
Epoch 94/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0725 - accuracy: 0.9689
Epoch 95/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0704 - accuracy: 0.9710
Epoch 96/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0728 - accuracy: 0.9679
Epoch 97/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0699 - accuracy: 0.9689
Epoch 98/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0735 - accuracy: 0.9699
Epoch 99/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0708 - accuracy: 0.9699
Epoch 100/100
33/33 [==============================] - 0s 1ms/step - loss: 0.0699 - accuracy: 0.9699
```

Out[165]: <tensorflow.python.keras.callbacks.History at 0x1d1fc6c60c8>

Multi Layer Perceptron Evaluation Metrics

In [166]:
```
model1.evaluate(X_train, y_train)
```

```
31/31 [==============================] - 0s 740us/step - loss: 0.0652 - accuracy: 0.9720
```

Out[166]: [0.0652037039399147, 0.9720207452774048]

In [167]:
```
model1.evaluate(X_test, y_test)
```

```
8/8 [==============================] - 0s 1ms/step - loss: 0.4219 - accuracy: 0.9298
```

Out[167]: [0.42187103629112244, 0.9297520518302917]

Multi Layer Perceptron Precision Scores

In [168]:
```
train_pred=model1.predict_classes(X_train)
pred=model1.predict_classes(X_test)
```

In [169]:
```
print("train",precision_score(y_train, train_pred))
print("test",precision_score(y_test,pred))
```

```
train 0.941320293398533
test 0.8936170212765957
```

In [170]:
```
from sklearn.metrics import recall_score
print("train",recall_score(y_train, train_pred))
print("test",recall_score(y_test,pred))
```

```
train 0.9922680412371134
test 0.9230769230769230
```