In [40]:

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
```

In [2]:

```
df = pd.read_csv('Bank Customer Churn Prediction.csv')
```

In [521]:

```
df.head()
```

Out[521]:

	customer_id	credit_score	country	gender	age	tenure	balance	products_number	credi
0	15634602	619	1	0	42	2	0.00	1	
1	15647311	608	2	0	41	1	83807.86	1	
2	15619304	502	1	0	42	8	159660.80	3	
3	15701354	699	1	0	39	1	0.00	2	
4	15737888	850	2	0	43	2	125510.82	1	

In [520]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9930 entries, 0 to 9999
Data columns (total 12 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   customer_id       9930 non-null   int64  
 1   credit_score      9930 non-null   int64  
 2   country           9930 non-null   int64  
 3   gender            9930 non-null   int64  
 4   age               9930 non-null   int64  
 5   tenure            9930 non-null   int64  
 6   balance           9930 non-null   float64
 7   products_number   9930 non-null   int64  
 8   credit_card       9930 non-null   int64  
 9   active_member     9930 non-null   int64  
 10  estimated_salary  9930 non-null   float64
 11  churn             9930 non-null   int64  
dtypes: float64(2), int64(10)
memory usage: 1.2 MB
```

In [5]:

```
df.describe()
```

Out[5]:

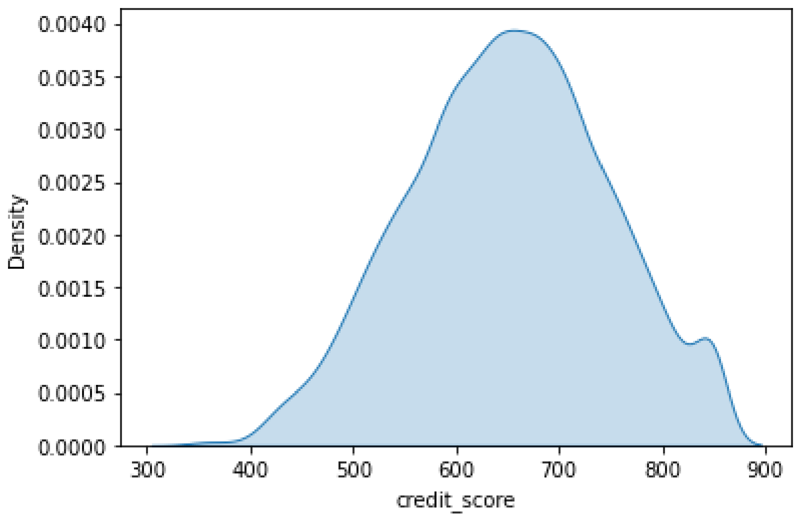
	customer_id	credit_score	age	tenure	balance	products_numb
count	1.000000e+04	10000.000000	10000.000000	10000.000000	10000.000000	10000.00000
mean	1.569094e+07	650.528800	38.921800	5.012800	76485.889288	1.53020
std	7.193619e+04	96.653299	10.487806	2.892174	62397.405202	0.58165
min	1.556570e+07	350.000000	18.000000	0.000000	0.000000	1.00000
25%	1.562853e+07	584.000000	32.000000	3.000000	0.000000	1.00000
50%	1.569074e+07	652.000000	37.000000	5.000000	97198.540000	1.00000
75%	1.575323e+07	718.000000	44.000000	7.000000	127644.240000	2.00000
max	1.581569e+07	850.000000	92.000000	10.000000	250898.090000	4.00000

In [8]:

```
sns.kdeplot(data = df.credit_score,shade=True)
```

Out[8]:

<AxesSubplot:xlabel='credit_score', ylabel='Density'>

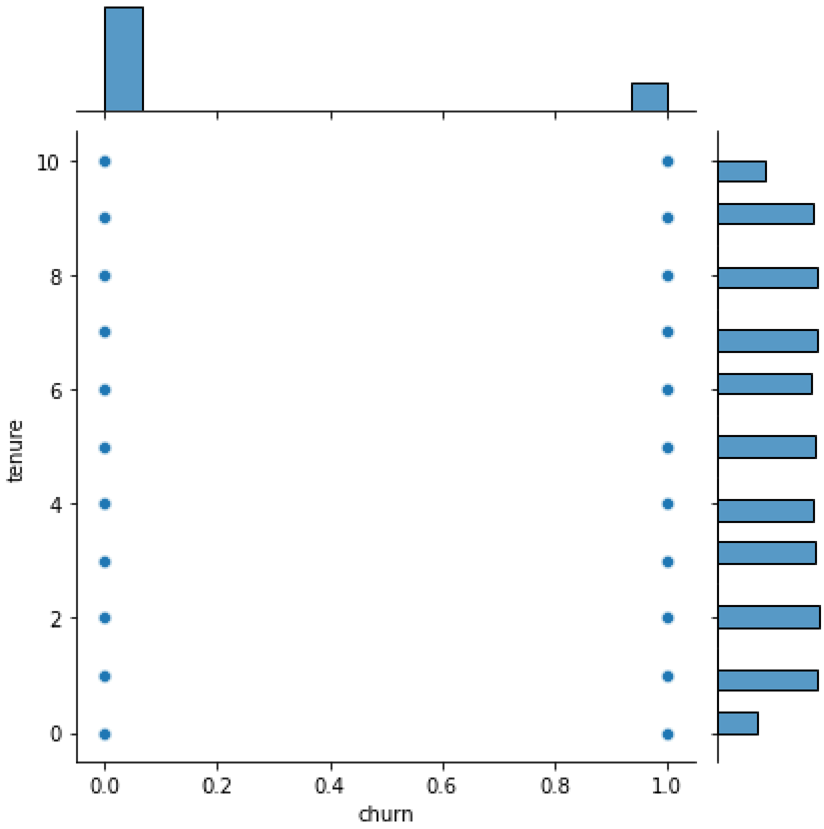


In [519]:

```
sns.jointplot(data=df,x=df.churn,y=df.tenure)
```

Out[519]:

```
<seaborn.axisgrid.JointGrid at 0x1659043b910>
```



In [11]:

```
df.columns
```

Out[11]:

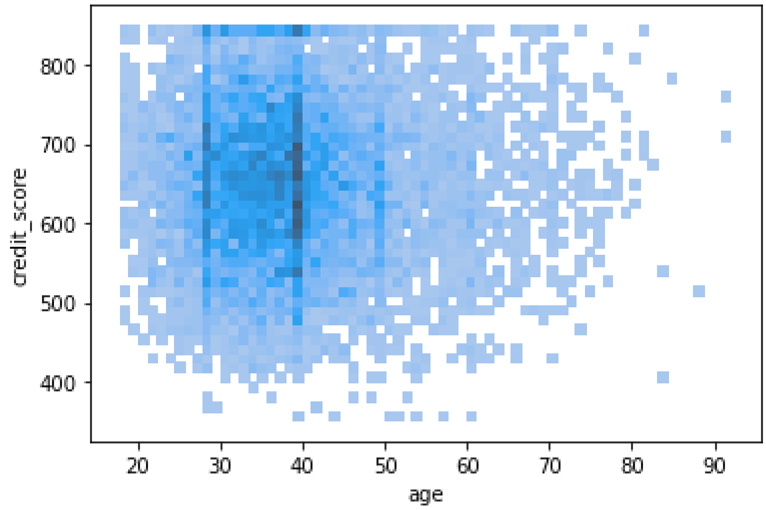
```
Index(['customer_id', 'credit_score', 'country', 'gender', 'age', 'tenure',
       'balance', 'products_number', 'credit_card', 'active_member',
       'estimated_salary', 'churn'],
      dtype='object')
```

In [31]:

```
sns.histplot(x=df.age,y=df.credit_score)
```

Out[31]:

```
<AxesSubplot:xlabel='age', ylabel='credit_score'>
```

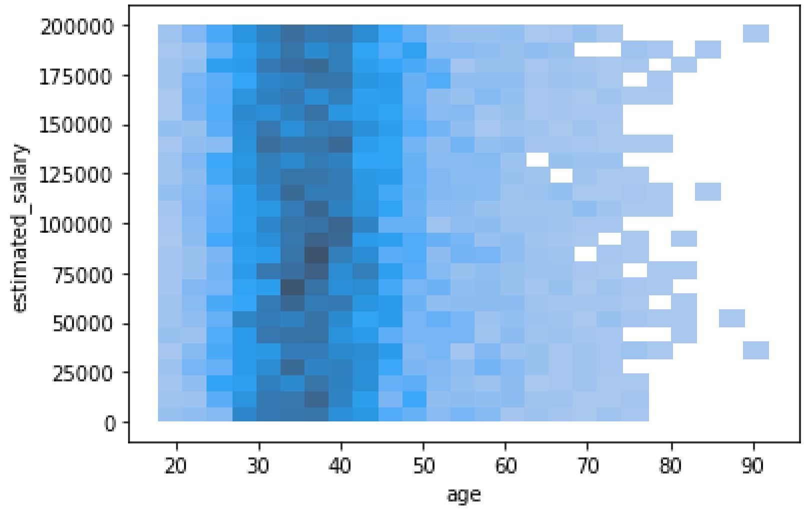


In [34]:

```
sns.histplot(x=df.age,y=df.estimated_salary,bins=25)
```

Out[34]:

```
<AxesSubplot:xlabel='age', ylabel='estimated_salary'>
```



In [64]:

```
kd = df.select_dtypes(include=['int64'])
kd
kd.drop(columns=['customer_id'],inplace=True)
```

In [47]:

```
np.corrcoef(df.age,df.churn)
```

Out[47]:

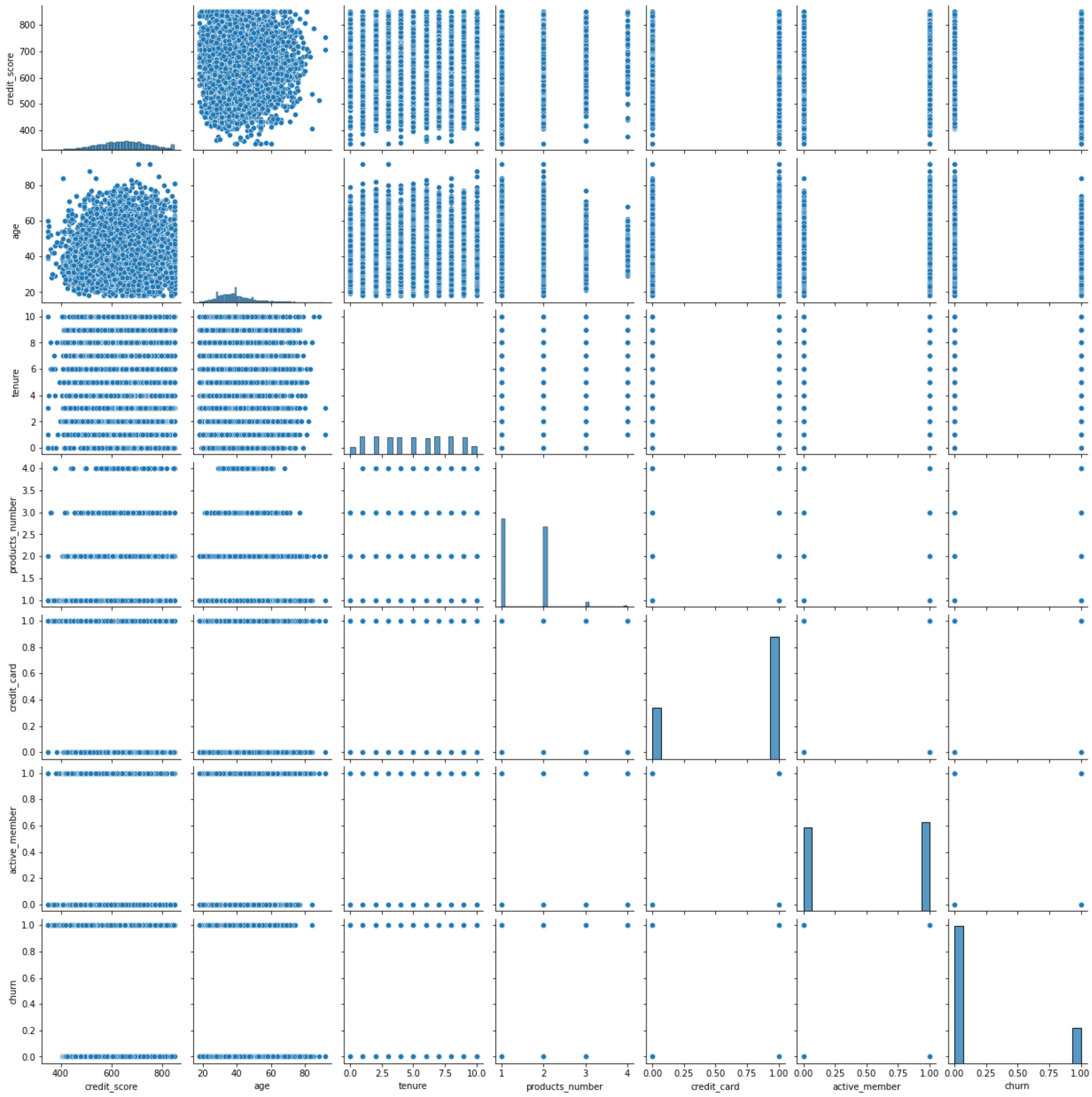
```
array([[1.        , 0.28532304],
       [0.28532304, 1.        ]])
```

In [65]:

```
sns.pairplot(kd)
plt.figure(figsize = (20,10))
```

Out[65]:

```
<Figure size 1440x720 with 0 Axes>
```




```
<Figure size 1440x720 with 0 Axes>
```

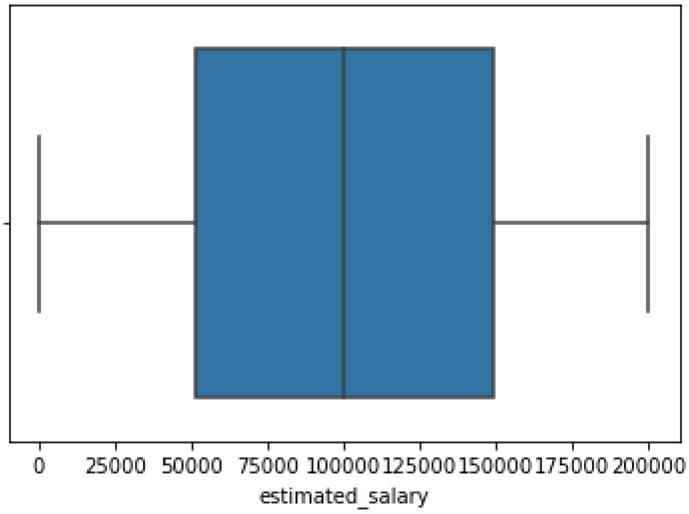
Check outliers in important features

In [404]:

```
sns.boxplot(x=df['estimated_salary'])
```

Out[404]:

<AxesSubplot:xlabel='estimated_salary'>

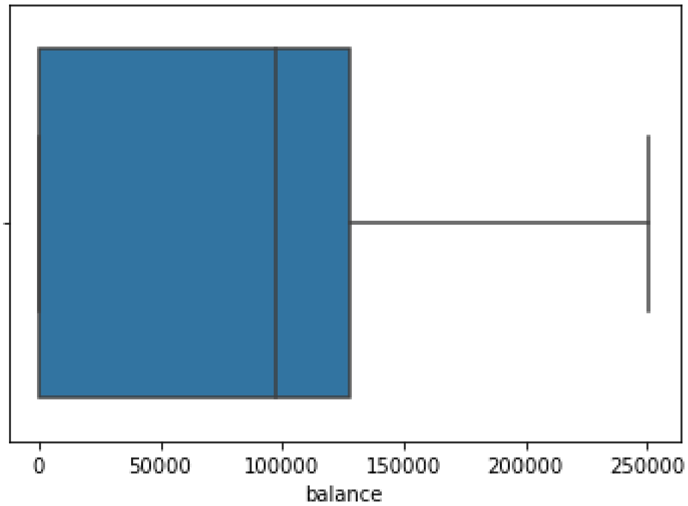


In [405]:

```
sns.boxplot(x=df['balance'])
```

Out[405]:

<AxesSubplot:xlabel='balance'>

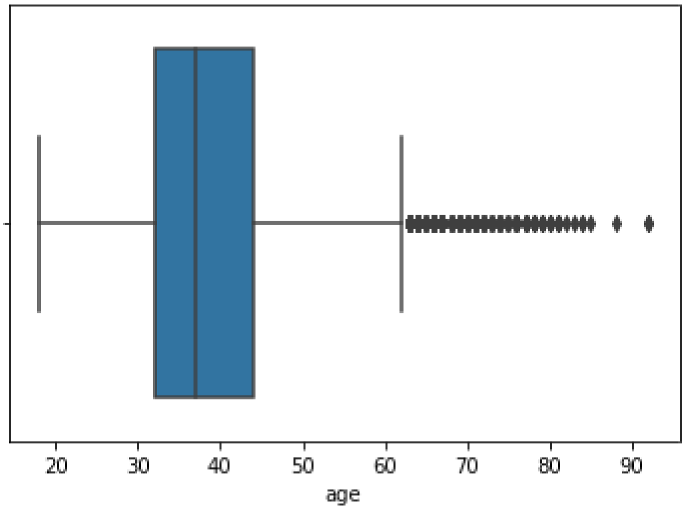


In [406]:

```
sns.boxplot(x=df['age'])
```

Out[406]:

```
<AxesSubplot:xlabel='age'>
```



In [408]:

```
df[df.age>70].age.value_counts()
```

Out[408]:

```
71    27
72    21
74    18
73    13
76    11
77    10
75     9
78     5
81     4
79     4
80     3
84     2
92     2
82     1
83     1
85     1
88     1
Name: age, dtype: int64
```

In [428]:

```
df.shape
```

Out[428]:

```
(9930, 12)
```

In [429]:

```
df.columns
```

Out[429]:

```
Index(['customer_id', 'credit_score', 'country', 'gender', 'age', 'tenure',
       'balance', 'products_number', 'credit_card', 'active_member',
       'estimated_salary', 'churn'],
      dtype='object')
```

In [430]:

```
df.country.value_counts()
```

Out[430]:

```
1    4984
3    2485
2    2461
Name: country, dtype: int64
```

In [431]:

```
df.products_number[df.churn == 1].value_counts()
```

Out[431]:

```
1    1399
2     348
3     218
4      59
Name: products_number, dtype: int64
```

In [432]:

```
df.products_number.value_counts()
```

Out[432]:

```
1    5048
2    4559
3     264
4      59
Name: products_number, dtype: int64
```

In [433]:

```
df.gender[df.churn == 1].value_counts()
```

Out[433]:

```
0    1129
1     895
Name: gender, dtype: int64
```

More number of females are founded to be churn customers

In [434]:

```
df[df.churn==1].groupby('country')['products_number','credit_score','age','tenure',].mean()
```

```
<ipython-input-434-2d01a026bb29>:1: FutureWarning: Indexing with multiple ke
ys (implicitly converted to a tuple of keys) will be deprecated, use a list
instead.
  df[df.churn==1].groupby('country')['products_number','credit_score','ag
e','tenure',].mean()
```

Out[434]:

	products_number	credit_score	age	tenure
country				
1	1.477019	641.930435	45.136646	5.011180
2	1.512195	648.290244	44.121951	4.663415
3	1.453646	647.415328	44.915946	5.001236

In [435]:

```
df.country[df.churn==1].value_counts()
```

Out[435]:

```
3    809
1    805
2    410
Name: country, dtype: int64
```

Comparitively less number of churn customers from spain almost half from other 2 countries

In [436]:

```
df.credit_score[df.churn==1].value_counts()
```

Out[436]:

```
850    43
651    17
705    16
727    13
625    13
       ..
437     1
436     1
367     1
431     1
522     1
Name: credit_score, Length: 420, dtype: int64
```

Possibility that people with low credit score are less likely to be churn customers

In [437]:

```
df[df.churn==1].groupby('gender')['products_number','credit_score','age','tenure',].mean()
```

```
<ipython-input-437-77e00ecc3223>:1: FutureWarning: Indexing with multiple ke
ys (implicitly converted to a tuple of keys) will be deprecated, use a list
instead.
  df[df.churn==1].groupby('gender')['products_number','credit_score','ag
e','tenure',].mean()
```

Out[437]:

	products_number	credit_score	age	tenure
gender				
0	1.511957	647.054916	44.798937	4.937112
1	1.427933	643.337430	44.898324	4.936313

In [438]:

```
df[df.churn==0].groupby('gender')['products_number','credit_score','age','tenure',].mean()
```

```
<ipython-input-438-d54be157b625>:1: FutureWarning: Indexing with multiple ke
ys (implicitly converted to a tuple of keys) will be deprecated, use a list
instead.
  df[df.churn==0].groupby('gender')['products_number','credit_score','ag
e','tenure',].mean()
```

Out[438]:

	products_number	credit_score	age	tenure
gender				
0	1.554338	652.211726	37.384661	4.975126
1	1.536763	651.727534	37.422610	5.074189

In [439]:

```
df.active_member[df.churn==1].value_counts()
```

Out[439]:

```
0    1291
1     733
Name: active_member, dtype: int64
```

In [440]:

```
df['gender'].replace(['Male','Female'],[1,0],inplace=True)

df
```

Out[440]:

	customer_id	credit_score	country	gender	age	tenure	balance	products_number	credit_card	ac
0	15634602	619	1	0	42	2	0.00	1	1	
1	15647311	608	2	0	41	1	83807.86	1	0	
2	15619304	502	1	0	42	8	159660.80	3	1	
3	15701354	699	1	0	39	1	0.00	2	0	
4	15737888	850	2	0	43	2	125510.82	1	1	
...	...	...	...	...	...	...	...	...	...	
9995	15606229	771	1	1	39	5	0.00	2	1	
9996	15569892	516	1	1	35	10	57369.61	1	1	
9997	15584532	709	1	0	36	7	0.00	1	0	

In [485]:

```
df['country'].replace(['France','Spain','Germany'],[1,2,3],inplace=True)
df
```

Out[485]:

	customer_id	credit_score	country	gender	age	tenure	balance	products_number	cı
0	15634602	619	1	0	42	2	0.00	1	
1	15647311	608	2	0	41	1	83807.86	1	
2	15619304	502	1	0	42	8	159660.80	3	
3	15701354	699	1	0	39	1	0.00	2	
4	15737888	850	2	0	43	2	125510.82	1	
...	...	...	...	...	...	...	...	...	
9995	15606229	771	1	1	39	5	0.00	2	
9996	15569892	516	1	1	35	10	57369.61	1	
9997	15584532	709	1	0	36	7	0.00	1	
9998	15682355	772	3	1	42	3	75075.31	2	
9999	15628319	792	1	0	28	4	130142.79	1	

9930 rows × 12 columns

In active members can be considered as churn customers

Now we will extract our features for our model

In [488]:

```
lf[['credit_score','tenure','active_member','age','country','gender','credit_card','estimate
```

Out[488]:

	credit_score	tenure	active_member	age	country	gender	credit_card	estimated_salary
0	619	2	1	42	1	0	1	101348.88
1	608	1	1	41	2	0	0	112542.58
2	502	8	0	42	1	0	1	113931.57
3	699	1	0	39	1	0	0	93826.63
4	850	2	1	43	2	0	1	79084.10
...	...	...	...	...	...	...	...	...
9995	771	5	0	39	1	1	1	96270.64
9996	516	10	1	35	1	1	1	101699.77
9997	709	7	1	36	1	0	0	42085.58
9998	772	3	0	42	3	1	1	92888.52
9999	792	4	0	28	1	0	1	38190.78

9930 rows × 10 columns

Logistic regression

In [489]:

```
from sklearn.linear_model import LogisticRegression
model = LogisticRegression(random_state=0)
```

In [490]:

```
from sklearn.model_selection import train_test_split
train_x,test_x,train_y,test_y = train_test_split(X,y)
```

In [491]:

```
model.fit(train_x,train_y)
```

Out[491]:

```
LogisticRegression(random_state=0)
```

In [492]:

```
y_predict = model.predict(test_x)
y_predict[0:10]
```

Out[492]:

```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0], dtype=int64)
```

In [493]:

```
from sklearn.metrics import mean_absolute_error
mae = mean_absolute_error(test_y,y_predict)
mae
```

Out[493]:

```
0.20338300443012486
```

In [494]:

```
from sklearn.metrics import accuracy_score
acs = accuracy_score(test_y,y_predict)
acs
```

Out[494]:

```
0.7966169955698752
```

In [ ]:

```

```

Decision Tree Classification

In [495]:

```
from sklearn.tree import DecisionTreeClassifier
model_dtc = DecisionTreeClassifier(random_state=0)
model_dtc
```

Out[495]:

```
DecisionTreeClassifier(random_state=0)
```

In [496]:

```
model_dtc.fit(train_x,train_y)
```

Out[496]:

```
DecisionTreeClassifier(random_state=0)
```

In [497]:

```
y_pred_dtc = model_dtc.predict(test_x)
y_pred_dtc
```

Out[497]:

```
array([0, 0, 0, ..., 0, 0, 0], dtype=int64)
```

In [498]:

```
mae_dtc = mean_absolute_error(test_y,y_pred_dtc)
mae_dtc
```

Out[498]:

```
0.2057994361659283
```

In [499]:

```
acs_dtc = accuracy_score(test_y,y_pred_dtc)
acs_dtc
```

Out[499]:

```
0.7942005638340717
```

In [ ]:

```

```

Randomforest classifier

In [500]:

```
from sklearn.ensemble import RandomForestClassifier
model_rfc = RandomForestClassifier(random_state=1)
```

In [501]:

```
model_rfc.fit(train_x,train_y)
```

Out[501]:

```
RandomForestClassifier(random_state=1)
```

In [502]:

```
y_pred_rfc = model.predict(test_x)
```

In [503]:

```
mae_rfc = mean_absolute_error(test_y,y_pred_rfc)
mae_rfc
```

Out[503]:

```
0.20338300443012486
```

In [504]:

```
acs_rfc = accuracy_score(test_y,y_pred_rfc)
acs_rfc
```

Out[504]:

```
0.7966169955698752
```

Support Vector Machine

In [505]:

```
from sklearn.svm import SVC
model_svm = SVC()
```

In [506]:

```
model_svm.fit(train_x,train_y)
```

Out[506]:

```
SVC()
```

In [507]:

```
y_pred_svm = model_svm.predict(test_x)
```

In [508]:

```
mae_svm = mean_absolute_error(test_y,y_pred_svm)
mae_svm
```

Out[508]:

```
0.19170358437374144
```

In [509]:

```
acs_svm = accuracy_score(test_y,y_pred_svm)
acs_svm
```

Out[509]:

```
0.8082964156262585
```

KNN

In [510]:

```
from sklearn.neighbors import KNeighborsClassifier
model_knc = KNeighborsClassifier()
```

In [511]:

```
model_knc.fit(train_x,train_y)
```

Out[511]:

```
KNeighborsClassifier()
```

In [512]:

```
y_pred_knc = model_knc.predict(test_x)
```

In [513]:

```
mae_knc = mean_absolute_error(test_y,y_pred_knc)
mae_knc
```

Out[513]:

```
0.23238018525976642
```

Naive Bayes

In [514]:

```
from sklearn.naive_bayes import BernoulliNB
model_nb = BernoulliNB()
```

In [515]:

```
model_nb.fit(train_x,train_y)
```

Out[515]:

```
BernoulliNB()
```

In [516]:

```
y_p_nb = model_nb.predict(test_x)
```

In [517]:

```
mae_nb = mean_absolute_error(test_y,y_p_nb)
mae_nb
```

Out[517]:

```
0.19170358437374144
```

In [ ]:

```

```

In [518]:

```
ddd = pd.DataFrame({
    'Naive Bayes': (1-mae_nb)*100,
    'KNN':(1-mae_knc)*100,
    'SVM':acs_svm*100,
    'Random_forest':acs_rfc*100,
    'DecisionTree':acs_dtc*100,
    "LogisticRegression":acs*100

},index=['Accuracy'])
ddd.T
```

Out[518]:

	Accuracy
Naive Bayes	80.829642
KNN	76.761981
SVM	80.829642
Random_forest	79.661700
DecisionTree	79.420056
LogisticRegression	79.661700

We are getting maximum accuracy from Naive Bayes And SVM

In [ ]: