ENTRANCE TEST (No.2)

Customer churn prediction

Declare libraries

In [171]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import matplotlib.ticker as ticker
from sklearn.neighbors import KNeighborsClassifier
from sklearn.preprocessing import MinMaxScaler, RobustScaler, StandardScaler
from sklearn.preprocessing import LabelEncoder, OneHotEncoder, OrdinalEncoder
from sklearn import tree
from sklearn.metrics import confusion_matrix
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import accuracy_score, classification_report
from sklearn.linear_model import LinearRegression
from lightgbm import LGBMClassifier
```

Import data

In [172]:
```
df1 = pd.read_csv("churn-bigml-80.csv")
df2 = pd.read_csv("churn-bigml-20.csv")

# merge data
df_train = pd.concat ([df1, df2], axis=0, ignore_index=True)

print("number of samples and number of data attributes Df",df_train.shape)
```

```
number of samples and number of data attributes Df (3333, 20)
```

Print out the first 10 lines of data

In [173]:
```
df_train.head(10)
```

Out[173]:

	State	Account length	Area code	International plan	Voice mail plan	Number vmail messages	Total day minutes	Total day calls	Total day charge	Total eve minutes	Total eve calls	Total eve charge	Total night minutes	To nig ca
0	KS	128	415	No	Yes	25	265.1	110	45.07	197.4	99	16.78	244.7	
1	OH	107	415	No	Yes	26	161.6	123	27.47	195.5	103	16.62	254.4	1
2	NJ	137	415	No	No	0	243.4	114	41.38	121.2	110	10.30	162.6	1
3	OH	84	408	Yes	No	0	299.4	71	50.90	61.9	88	5.26	196.9	
4	OK	75	415	Yes	No	0	166.7	113	28.34	148.3	122	12.61	186.9	1
5	AL	118	510	Yes	No	0	223.4	98	37.98	220.6	101	18.75	203.9	1
6	MA	121	510	No	Yes	24	218.2	88	37.09	348.5	108	29.62	212.6	
7	MO	147	415	Yes	No	0	157.0	79	26.69	103.1	94	8.76	211.8	
8	WV	141	415	Yes	Yes	37	258.6	84	43.96	222.0	111	18.87	326.4	
9	RI	74	415	No	No	0	187.7	127	31.91	163.4	148	13.89	196.0	

Overview of the data frame

In [174]:
```
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 20 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   State                   3333 non-null   object
 1   Account length          3333 non-null   int64
 2   Area code               3333 non-null   int64
 3   International plan      3333 non-null   object
 4   Voice mail plan         3333 non-null   object
 5   Number vmail messages   3333 non-null   int64
 6   Total day minutes       3333 non-null   float64
 7   Total day calls         3333 non-null   int64
 8   Total day charge        3333 non-null   float64
 9   Total eve minutes       3333 non-null   float64
 10  Total eve calls         3333 non-null   int64
 11  Total eve charge        3333 non-null   float64
 12  Total night minutes     3333 non-null   float64
 13  Total night calls       3333 non-null   int64
 14  Total night charge      3333 non-null   float64
 15  Total intl minutes      3333 non-null   float64
 16  Total intl calls        3333 non-null   int64
 17  Total intl charge       3333 non-null   float64
 18  Customer service calls  3333 non-null   int64
 19  Churn                   3333 non-null   bool
dtypes: bool(1), float64(8), int64(8), object(3)
memory usage: 498.1+ KB
```

Check for missing values

In [175]:
```
df_train.dropna(inplace=True)
# detect missing values of the whole table
df_train.count()
```

Out[175]:
```
State                   3333
Account length          3333
Area code               3333
International plan      3333
Voice mail plan         3333
Number vmail messages   3333
Total day minutes       3333
Total day calls         3333
Total day charge        3333
Total eve minutes       3333
Total eve calls         3333
Total eve charge        3333
Total night minutes     3333
Total night calls       3333
Total night charge      3333
Total intl minutes      3333
Total intl calls        3333
Total intl charge       3333
Customer service calls  3333
Churn                   3333
dtype: int64
```

Statistics of quantitative values

In [176]:
```
df_train.describe()
```

Out[176]:

	Account length	Area code	Number vmail messages	Total day minutes	Total day calls	Total day charge	Total eve minutes	Total eve calls	T
count	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333
mean	101.064806	437.182418	8.099010	179.775098	100.435644	30.562307	200.980348	100.114311	17
std	39.822106	42.371290	13.688365	54.467389	20.069084	9.259435	50.713844	19.922625	4
min	1.000000	408.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0
25%	74.000000	408.000000	0.000000	143.700000	87.000000	24.430000	166.600000	87.000000	14
50%	101.000000	415.000000	0.000000	179.400000	101.000000	30.500000	201.400000	100.000000	17
75%	127.000000	510.000000	20.000000	216.400000	114.000000	36.790000	235.300000	114.000000	20
max	243.000000	510.000000	51.000000	350.800000	165.000000	59.640000	363.700000	170.000000	30

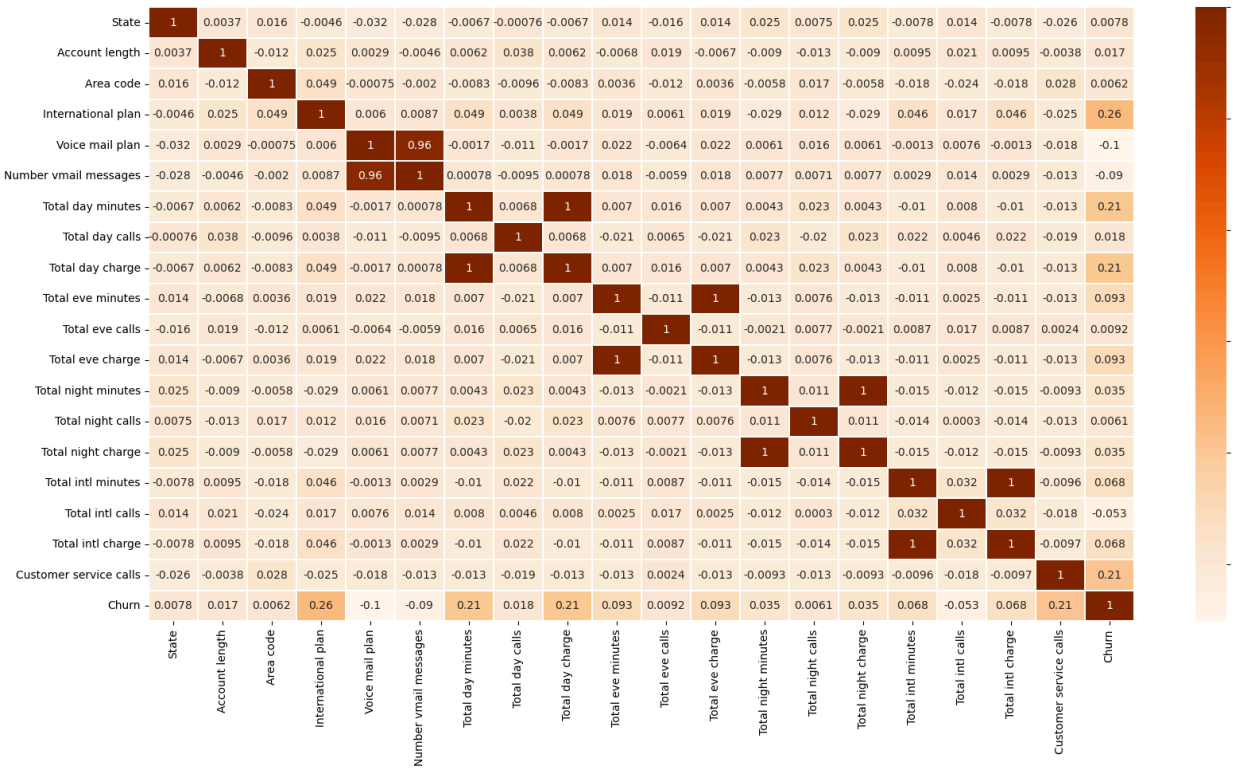
In [177]:
```
# Đổi dữ liệu từ dạng định danh (object) về dạng số
lb_make = LabelEncoder()
df_train["State"] = lb_make.fit_transform(df_train["State"])
df_train["International plan"] = lb_make.fit_transform(df_train["International plan"])
df_train["Voice mail plan"] = lb_make.fit_transform(df_train["Voice mail plan"])
df_train["Churn"] = lb_make.fit_transform(df_train["Churn"])
df_train.head(10)
```

Out[177]:

	State	Account length	Area code	International plan	Voice mail plan	Number vmail messages	Total day minutes	Total day calls	Total day charge	Total eve minutes	Total eve calls	Total eve charge	Total night minutes	To nig ca
0	16	128	415	0	1	25	265.1	110	45.07	197.4	99	16.78	244.7	
1	35	107	415	0	1	26	161.6	123	27.47	195.5	103	16.62	254.4	1
2	31	137	415	0	0	0	243.4	114	41.38	121.2	110	10.30	162.6	1
3	35	84	408	1	0	0	299.4	71	50.90	61.9	88	5.26	196.9	
4	36	75	415	1	0	0	166.7	113	28.34	148.3	122	12.61	186.9	1
5	1	118	510	1	0	0	223.4	98	37.98	220.6	101	18.75	203.9	1
6	19	121	510	0	1	24	218.2	88	37.09	348.5	108	29.62	212.6	1
7	24	147	415	1	0	0	157.0	79	26.69	103.1	94	8.76	211.8	
8	49	141	415	1	1	37	258.6	84	43.96	222.0	111	18.87	326.4	
9	39	74	415	0	0	0	187.7	127	31.91	163.4	148	13.89	196.0	

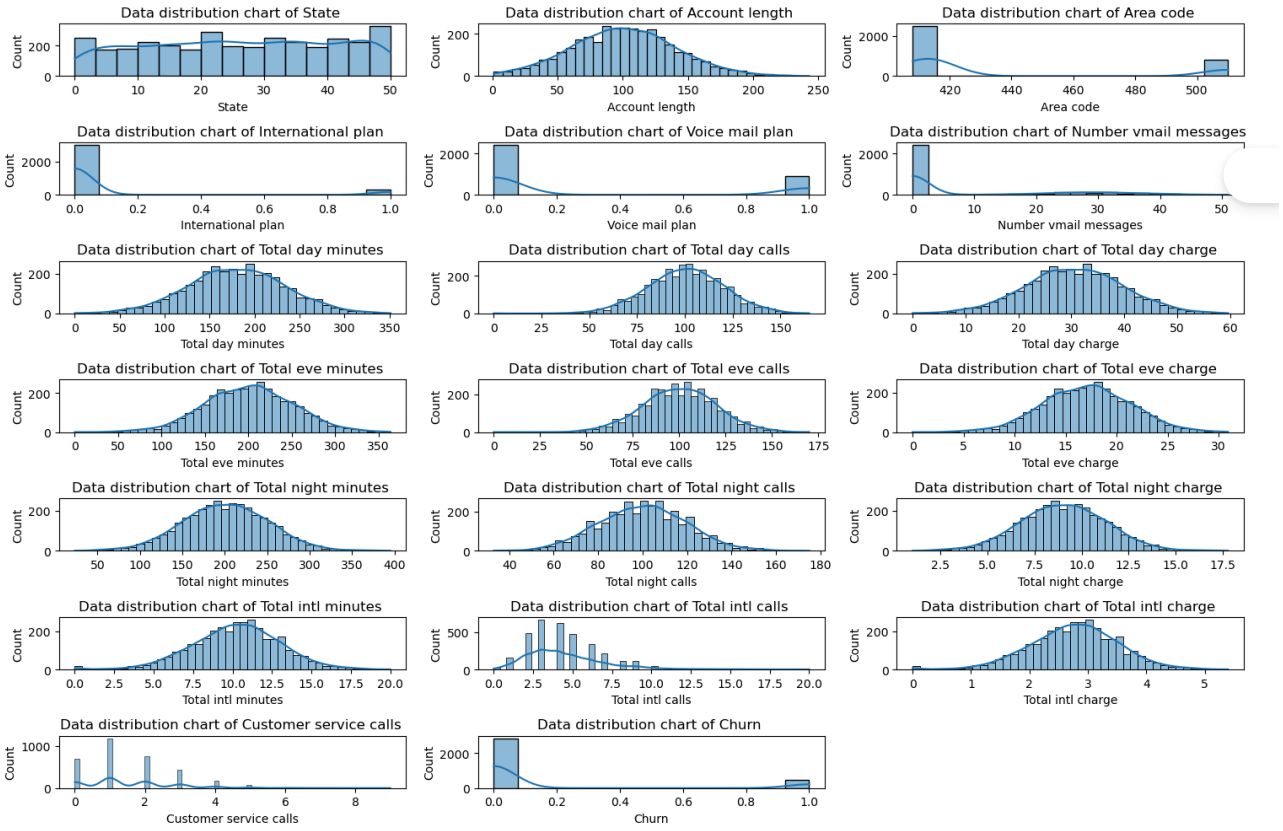
Statue matrix

In [178]:
```
corr = df_train.corr()
plt.figure(figsize = (20,10))
sns.heatmap(corr, annot = True, cmap = 'Oranges', linewidths=1.25)
plt.show()
```



Data distribution charts

In [179]:
```
plt.figure( figsize = (15, 10))
for i, col in enumerate (df_train.columns,1):
    plt.subplot(7,3,i)
    plt.title(f"Data distribution chart of {col} ")
    sns.histplot(df_train[col], kde=True)
    plt.tight_layout()
    plt.plot()
```



Decision Tree

In [180]:
```
# Divide the data set into train and test sets
y = df_train['Churn']
X = df_train.drop( columns=['Churn'])

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 0)

ro_scaler = RobustScaler()
X_train = ro_scaler.fit_transform(X_train)
X_test = ro_scaler.fit_transform(X_test)
print('Total data train : %i \nTotal data test : %i' % (X_train.shape[0],X_test.shape[1]))
```

```
Total data train : 2666
Total data test : 19
```

In [181]:
```
X_train
```

Out[181]:
```
array([[ 0.16      ,  0.37037037,  0.93137255, ...,  0.        ,
         0.30927835,  0.        ],
       [ 0.76      , -0.37037037,  0.        , ...,  0.        ,
         0.24742268,  0.        ],
       [-1.        ,  0.03703704, -0.06862745, ...,  0.66666667,
         1.50515464,  0.        ],
       ...,
       [-0.16      , -0.16666667, -0.06862745, ...,  0.33333333,
        -1.06185567,  1.        ],
       [ 0.32      ,  1.31481481,  0.        , ...,  0.33333333,
         0.80412371,  1.        ],
       [-0.88      ,  0.44444444, -0.06862745, ...,  0.        ,
         0.24742268,  0.        ]])
```

In [182]:
```
y_train
```

Out[182]:
```
1460    0
2000    0
666     0
2962    0
2773    0
       ..
835     0
3264    0
1653    0
2607    0
2732    0
Name: Churn, Length: 2666, dtype: int64
```

In [183]:
```
X_test
```

Out[183]:
```
array([[-9.43396226e-01, -1.14814815e+00,  0.00000000e+00, ...,
         3.33333333e-01,  3.15789474e-01,  0.00000000e+00],
       [-1.13207547e-01,  1.00000000e+00,  0.00000000e+00, ...,
         3.33333333e-01, -9.05263158e-01,  2.00000000e+00],
       [-6.79245283e-01,  9.25925926e-02, -7.00000000e+00, ...,
         1.00000000e+00,  1.56842105e+00, -1.00000000e+00],
       ...,
       [ 4.52830189e-01, -9.62962963e-01,  9.50000000e+01, ...,
         0.00000000e+00,  1.15789474e-01,  1.00000000e+00],
       [-6.79245283e-01, -8.88888889e-01,  9.50000000e+01, ...,
        -3.33333333e-01,  8.21052632e-01, -1.00000000e+00],
       [-8.30188679e-01, -1.11111111e+00,  0.00000000e+00, ...,
         3.33333333e-01, -5.68421053e-01, -1.00000000e+00]])
```

In [184]:
```
y_test
```

Out[184]:
```
405     0
118     0
710     0
499     0
2594    0
       ..
2255    0
242     0
1916    0
2160    0
1482    0
Name: Churn, Length: 667, dtype: int64
```

Declare the ID3 decision tree model

In [185]:
```
# Declare the model
model =tree.DecisionTreeClassifier(criterion ="entropy", random_state = 700, max_depth = 10, mi
```

In [186]:
```
# Model training
model = model.fit(X_train, y_train)
```

In [187]:
```
# Test the model
y_pred = model.predict(X_test)
print("The model predicted label value :\n ", y_pred)
print('Actual label value of the model : \n', y_test)
```

```
The model predicted label value :
  [0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 0 1 0 0 1 0 1 0 0 0 0 1
 0 0 0 0 0 0 1 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 1 0 1 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0 1 0 0 1 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 1 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 1 0 1 0 0 0
 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 1 0 0 0 1 0 0 0 0 0 0 1 0 0 0 1 0 1 0 1 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0
 0 1 1 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0
 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 1 1 0 0 1 0 0 0 0 0 0 1 0 0 0 0 0 0 1 1
 0 0 0 0 1 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0 1 1 0 1 1 0 0 0 0 0 0 0 1 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 1 0 0 0 0 0 0 1 0 0 0 0 0
 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 1 0 0 0 0 1 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0
 0 1 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0
 1 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 1 0 0 0
 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1
 0]
Actual label value of the model :
 405     0
118     0
710     0
499     0
2594    0
       ..
2255    0
242     0
1916    0
2160    0
1482    0
Name: Churn, Length: 667, dtype: int64
```

In [188]:
```
# Calculate the accuracy of the model
print('model accuracy is :', accuracy_score(y_test, y_pred)*100, '%')
```

```
model accuracy is : 93.85307346326837 %
```

In [189]:
```
# Confusion Matrix and Classification Report
print('Confusion Matrix: \n', confusion_matrix(y_test, y_pred))
print('Classification Report: \n ', classification_report(y_test, y_pred))
```

```
Confusion Matrix:
 [[559  15]
 [ 26  67]]
Classification Report:
                precision    recall  f1-score   support

           0       0.96      0.97      0.96       574
           1       0.82      0.72      0.77        93

    accuracy                           0.94       667
   macro avg       0.89      0.85      0.87       667
weighted avg       0.94      0.94      0.94       667
```

LGBM Classisfier

In [190]:
```
# Declare the model
model = LGBMClassifier(random_state = 700, max_depth = 10, num_leaves = 31)
```

In [191]:
```
# model execution
model.fit(X_train, y_train)
```

```
[LightGBM] [Warning] Accuracy may be bad since you didn't explicitly set num_leaves OR 2^max_d
epth > num_leaves. (num_leaves=31).
[LightGBM] [Warning] Accuracy may be bad since you didn't explicitly set num_leaves OR 2^max_d
epth > num_leaves. (num_leaves=31).
[LightGBM] [Info] Number of positive: 390, number of negative: 2276
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.000378
seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2436
[LightGBM] [Info] Number of data points in the train set: 2666, number of used features: 19
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.146287 -> initscore=-1.764028
[LightGBM] [Info] Start training from score -1.764028
```

Out[191]:

LGBMClassifier

```
LGBMClassifier(max_depth=10, random_state=700)
```

In [192]:
```
# Test the model
y_lgbm_pred = model.predict(X_test)

print("The model predicted label value :\n ", y_lgbm_pred)
print('Actual label value of the model : \n', y_test)
```

```
[LightGBM] [Warning] Accuracy may be bad since you didn't explicitly set num_leaves OR 2^max_d
epth > num_leaves. (num_leaves=31).
The model predicted label value :
  [0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 0 1 0 0 1 0 1 0 0 0 0 1
 0 0 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 1 0 1 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 1 0 1 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0
 0 1 0 0 1 1 0 0 0 0 0 1 0 0 0 1 0 1 0 1 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1
 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 1 1 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0
 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 1 0 0 0 0 0 0 1 0 0 0 0 0 0 1 1
 0 0 0 0 1 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0 1 1 0 1 0 0 0 0 0 0 0 1 1 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 1 1 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0 1 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 1 0 0 0 1 1 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0
 0 1 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 1 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 1 0 0 0
 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1
 0]
Actual label value of the model :
 405     0
118     0
710     0
499     0
2594    0
       ..
2255    0
242     0
1916    0
2160    0
1482    0
Name: Churn, Length: 667, dtype: int64
```

In [193]:
```
# Calculate the accuracy of the model
print('model accuracy is :', accuracy_score(y_test, y_lgbm_pred)*100, '%')
```

```
model accuracy is : 95.2023988005997 %
```

In [194]:
```
# Confusion Matrix and Classification Report
print('Confusion Matrix: \n', confusion_matrix(y_test, y_lgbm_pred))
print('Classification Report: \n ', classification_report(y_test, y_lgbm_pred))
```

```
Confusion Matrix:
 [[565   9]
 [ 23  70]]
Classification Report:
                precision    recall  f1-score   support

           0       0.96      0.98      0.97       574
           1       0.89      0.75      0.81        93

    accuracy                           0.95       667
   macro avg       0.92      0.87      0.89       667
weighted avg       0.95      0.95      0.95       667
```

Random Forest

In [195]:
```
dt = RandomForestClassifier(max_depth = 3, max_features = 4)
```

In [196]:
```
dt.fit(X_train, y_train)
```

Out[196]:
```
RandomForestClassifier(max_depth=3, max_features=4)
```

In [197]:
```
y_pred = dt.predict(X_test)
```

In [198]:
```
print(" Train score : ", dt.score(X_train, y_train), " Test Score : ", dt.score(X_test, y_test))
```

```
 Train score :  0.8859714928732183  Test Score :  0.904047976011994
```

In [199]:
```
# Calculate the accuracy of the model
print('model accuracy is :', accuracy_score(y_test, y_pred)*100, '%')
```

```
model accuracy is : 90.4047976011994 %
```

In [200]:
```
print('Confusion Matrix: \n', confusion_matrix(y_test, y_pred))
print('Classification Report: \n ', classification_report(y_test, y_pred))
```

```
Confusion Matrix:
 [[574   0]
 [ 64  29]]
Classification Report:
                precision    recall  f1-score   support

           0       0.90      1.00      0.95       574
           1       1.00      0.31      0.48        93

    accuracy                           0.90       667
   macro avg       0.95      0.66      0.71       667
weighted avg       0.91      0.90      0.88       667
```

In [201]:
```
# Find the best parameters of the model
pram_grid = {"max_depth" :[2,3,4], 'max_features' : [3,4,5]}
clf = RandomForestClassifier()

grid = GridSearchCV(estimator = clf, param_grid = pram_grid, cv = 5)
grid_result = grid.fit(X_train, y_train)

print(grid_result)
print("Best: %f using %s" %(grid_result.best_score_ , grid_result.best_params_))
```

```
GridSearchCV(cv=5, estimator=RandomForestClassifier(),
             param_grid={'max_depth': [2, 3, 4], 'max_features': [3, 4, 5]})
Best: 0.898349 using {'max_depth': 4, 'max_features': 5}
```

Run the model with parameters max_depth= 4, max_features=5

In [202]:
```
dt = RandomForestClassifier(max_depth = 4, max_features = 5)
```

In [203]:
```
dt.fit(X_train, y_train)
```

Out[203]:
```
RandomForestClassifier(max_depth=4, max_features=5)
```

In [204]:
```
y_pred = dt.predict(X_test)
print(" Train score : ", dt.score(X_train, y_train), " Test Score : ", dt.score(X_test, y_test)
```

```
 Train score :  0.9309827456864216  Test Score :  0.9250374812593704
```

In [205]:
```
# Calculate the accuracy of the model
print('model accuracy is :', accuracy_score(y_test, y_pred)*100, '%')
```

```
model accuracy is : 92.50374812593704 %
```

In [206]:
```
print('Confusion Matrix: \n', confusion_matrix(y_test, y_pred))
print('Classification Report: \n ', classification_report(y_test, y_pred))
```

```
Confusion Matrix:
 [[570   4]
 [ 46  47]]
Classification Report:
               precision    recall  f1-score   support

           0       0.93      0.99      0.96       574
           1       0.92      0.51      0.65        93

    accuracy                           0.93       667
   macro avg       0.92      0.75      0.81       667
weighted avg       0.92      0.93      0.92       667
```

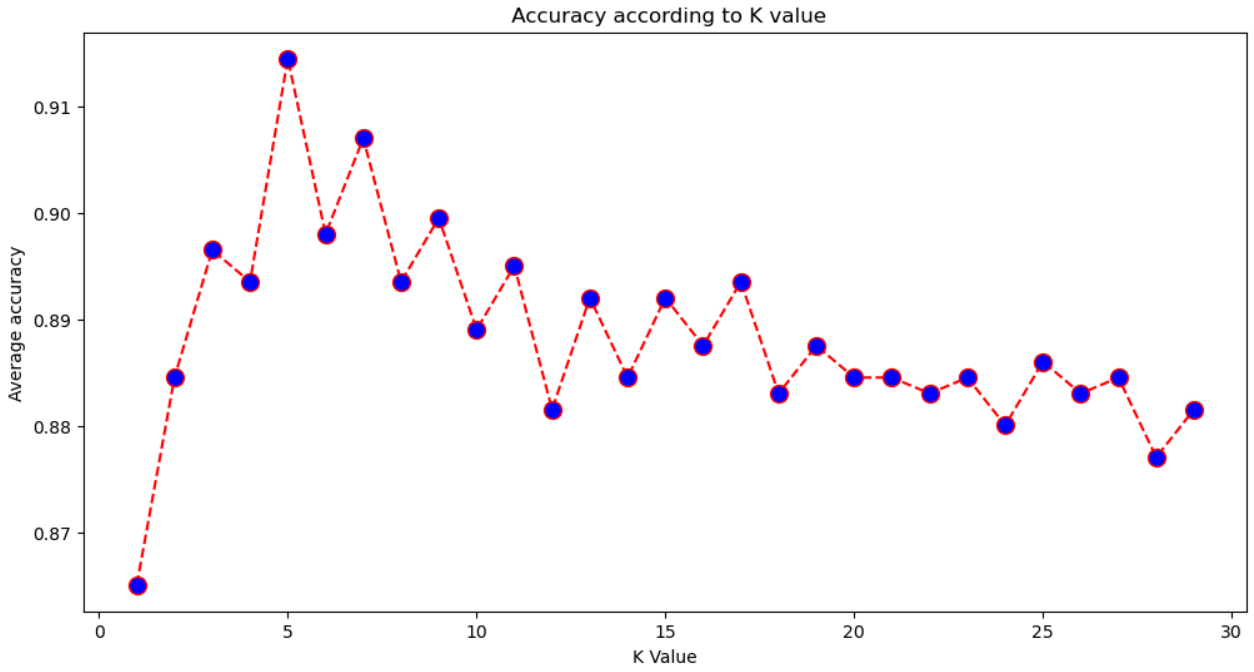
K-nearest neighbors

In [207]:
```
scores = []
for i in range(1,30):
    knn = KNeighborsClassifier(n_neighbors = i)
    knn.fit(X_train, y_train)
    y_pred = knn.predict(X_test)
    scores.append(accuracy_score(y_test, y_pred))
```

In [208]:
```
print(" Max Score :", max(scores), " at K = ", scores.index(max(scores)) +1)
plt.figure(figsize = (12,6))
plt.plot(range(1, 30), scores, color ='red', linestyle = 'dashed', marker ='o',
        markerfacecolor = 'blue', markersize = 10)
plt.title(' Accuracy according to K value')
plt.xlabel('K Value')
plt.ylabel('Average accuracy')
```

```
 Max Score : 0.9145427286356822  at K =  5
```

Out[208]:
```
Text(0, 0.5, 'Average accuracy')
```



In [209]:
```
knn = KNeighborsClassifier(n_neighbors = 5)
```

In [210]:
```
knn.fit(X_train, y_train)
```

Out[210]:
```
KNeighborsClassifier (https://scikit-learn.org/1.4/modules/generated/sklearn.neighbors.KNeighborsClassifier.html)
KNeighborsClassifier()
```

In [211]:
```
y_pred = knn.predict(X_test)
```

In [212]:
```
# Calculate the accuracy of the model
print('model accuracy is :', accuracy_score(y_test, y_pred)*100, '%')
```

```
model accuracy is : 91.45427286356822 %
```

In [213]:
```
print('Confusion Matrix: \n', confusion_matrix(y_test, y_pred))
print('Classification Report: \n ', classification_report(y_test, y_pred))
```

```
Confusion Matrix:
 [[572   2]
 [ 55  38]]
Classification Report:
                precision    recall  f1-score   support

           0       0.91      1.00      0.95       574
           1       0.95      0.41      0.57        93

    accuracy                           0.91       667
   macro avg       0.93      0.70      0.76       667
weighted avg       0.92      0.91      0.90       667
```