ASSIGNMENT 3

BANK MARKETING DATA SET

HANI NAFISAH AMALIYA

KELAS PYTN-10

Berikut ini merupakan Assignment 3 mengenai Membangun Model. Pada Assignment 3 ini, Membangun Model menggunakan :

1. Logistic Regression
2. K-Nearest Neighbors
3. Support Vector Machine
4. Decision Tree
5. Random Forest
6. Naive Bayes

In [1]:
```
# Import Library
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, normalize, StandardScaler
from sklearn import metrics
import statsmodels.api as sm
import warnings
warnings.filterwarnings("ignore")

%matplotlib inline
```

In [2]:
```
# Membaca File
df = pd.read_csv("./dataset/bank-additional/bank-additional/bank-addition
al-full.csv", sep=';')
df.tail(10)
```

Out[2]:

	age	job	marital	education	default	housing	loan	contact	mont
41178	62	retired	married	university.degree	no	no	no	cellular	nc
41179	64	retired	divorced	professional.course	no	yes	no	cellular	nc
41180	36	admin.	married	university.degree	no	no	no	cellular	nc
41181	37	admin.	married	university.degree	no	yes	no	cellular	nc
41182	29	unemployed	single	basic.4y	no	yes	no	cellular	nc
41183	73	retired	married	professional.course	no	yes	no	cellular	nc
41184	46	blue-collar	married	professional.course	no	no	no	cellular	nc
41185	56	retired	married	university.degree	no	yes	no	cellular	nc
41186	44	technician	married	professional.course	no	no	no	cellular	nc
41187	74	retired	married	professional.course	no	yes	no	cellular	nc

10 rows × 21 columns

In [3]:
```
df.columns
```

Out[3]:
```
Index(['age', 'job', 'marital', 'education', 'default', 'housing', 'loan
',
       'contact', 'month', 'day_of_week', 'duration', 'campaign', 'pdays
',
       'previous', 'poutcome', 'emp.var.rate', 'cons.price.idx',
       'cons.conf.idx', 'euribor3m', 'nr.employed', 'y'],
      dtype='object')
```

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41188 entries, 0 to 41187
Data columns (total 21 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   age             41188 non-null  int64  
 1   job             41188 non-null  object 
 2   marital         41188 non-null  object 
 3   education       41188 non-null  object 
 4   default         41188 non-null  object 
 5   housing         41188 non-null  object 
 6   loan            41188 non-null  object 
 7   contact         41188 non-null  object 
 8   month           41188 non-null  object 
 9   day_of_week     41188 non-null  object 
 10  duration        41188 non-null  int64  
 11  campaign        41188 non-null  int64  
 12  pdays           41188 non-null  int64  
 13  previous        41188 non-null  int64  
 14  poutcome        41188 non-null  object 
 15  emp.var.rate    41188 non-null  float64
 16  cons.price.idx  41188 non-null  float64
 17  cons.conf.idx   41188 non-null  float64
 18  euribor3m       41188 non-null  float64
 19  nr.employed     41188 non-null  float64
 20  y               41188 non-null  object 
dtypes: float64(5), int64(5), object(11)
memory usage: 6.6+ MB
```

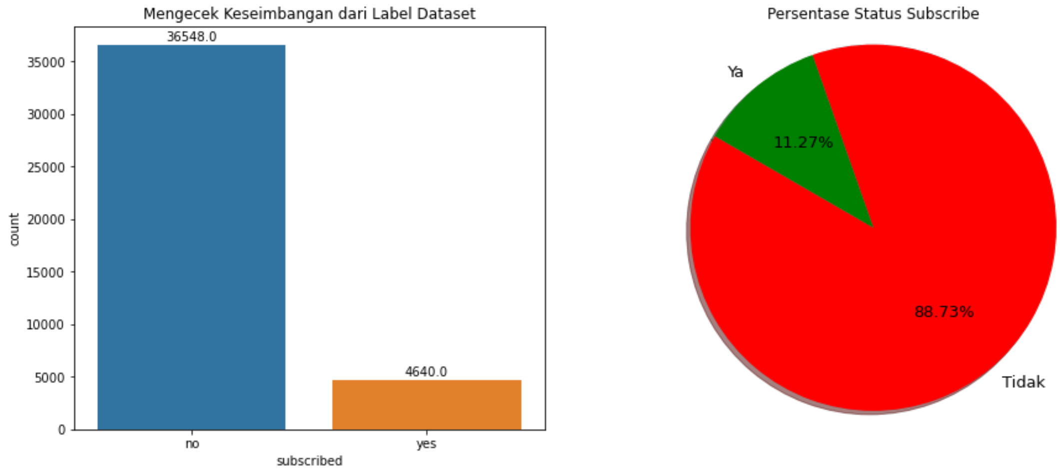
In [5]:
```
df.isnull().sum()
```

Out[5]:
```
age               0
job               0
marital           0
education         0
default           0
housing           0
loan              0
contact           0
month             0
day_of_week       0
duration          0
campaign          0
pdays             0
previous          0
poutcome          0
emp.var.rate      0
cons.price.idx    0
cons.conf.idx     0
euribor3m         0
nr.employed       0
y                 0
dtype: int64
```

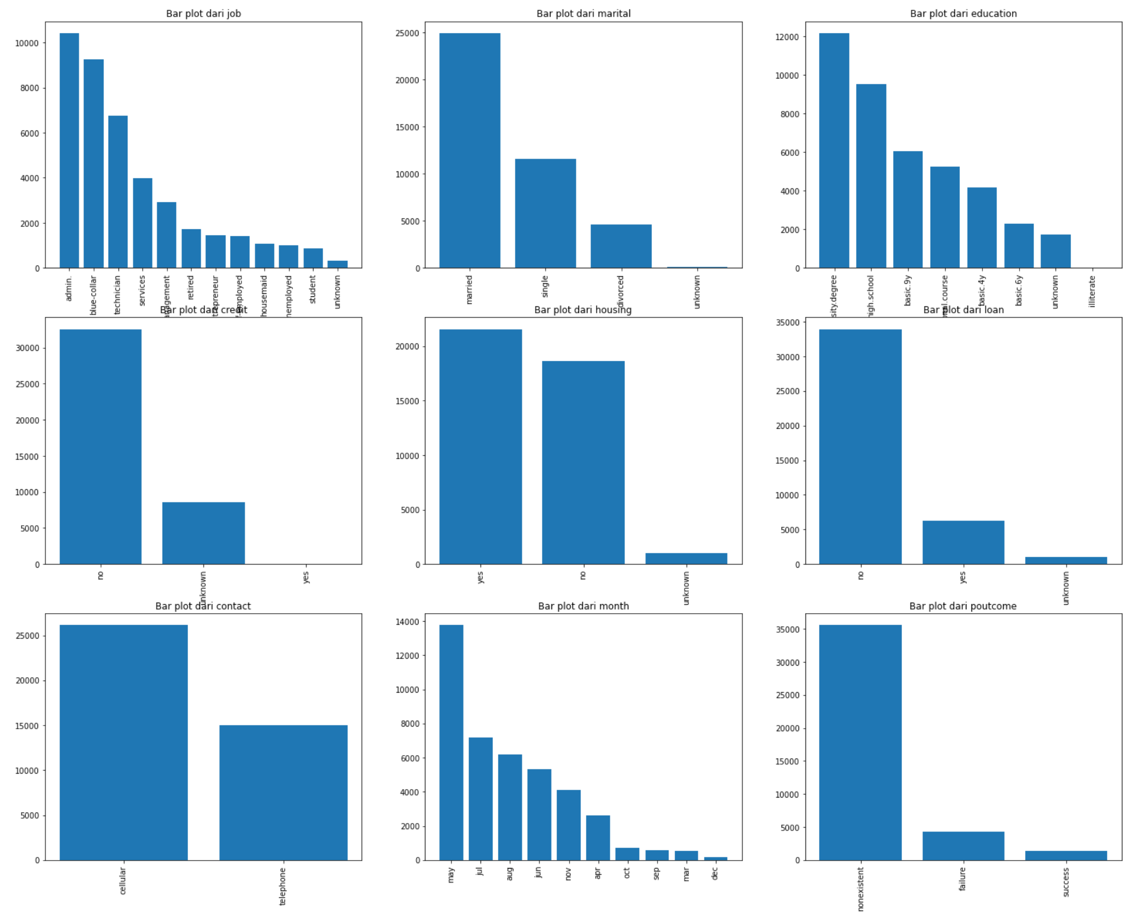
In [6]:
```
df.rename(columns={"default":"credit", "y":"subscribed"}, inplace=True)
```

In [7]:

```
# Mengecek keseimbangan jumlah label/output dataset
plt.rcParams['figure.figsize']=(15,6)
plt.subplot(121)
plt.title("Mengecek Keseimbangan dari Label Dataset")
ax = sns.countplot(x='subscribed', data=df)
for i in ax.patches:
    ax.annotate(format(i.get_height(),'0.1f'), (i.get_x() + i.get_width
()/2.,i.get_height()),
                ha='center', va='center', xytext=(0,7), textcoords='offset
points')

plt.subplot(122)
plt.title("Persentase Status Subscribe")
subscribed_values_count = df['subscribed'].value_counts()
subscribed_size = subscribed_values_count.values.tolist()
subscribed_labels = 'Tidak', 'Ya'
colors=['red', 'green']
pcs, texts, autotexts = plt.pie(subscribed_size, labels=subscribed_label
s, colors=colors,
                             autopct='%2.2f%%', shadow=True, startangle=1
50)

for text, autotext in zip(texts, autotexts):
    text.set_fontsize(13)
    autotext.set_fontsize(13)

plt.axis('equal')
plt.show()
```

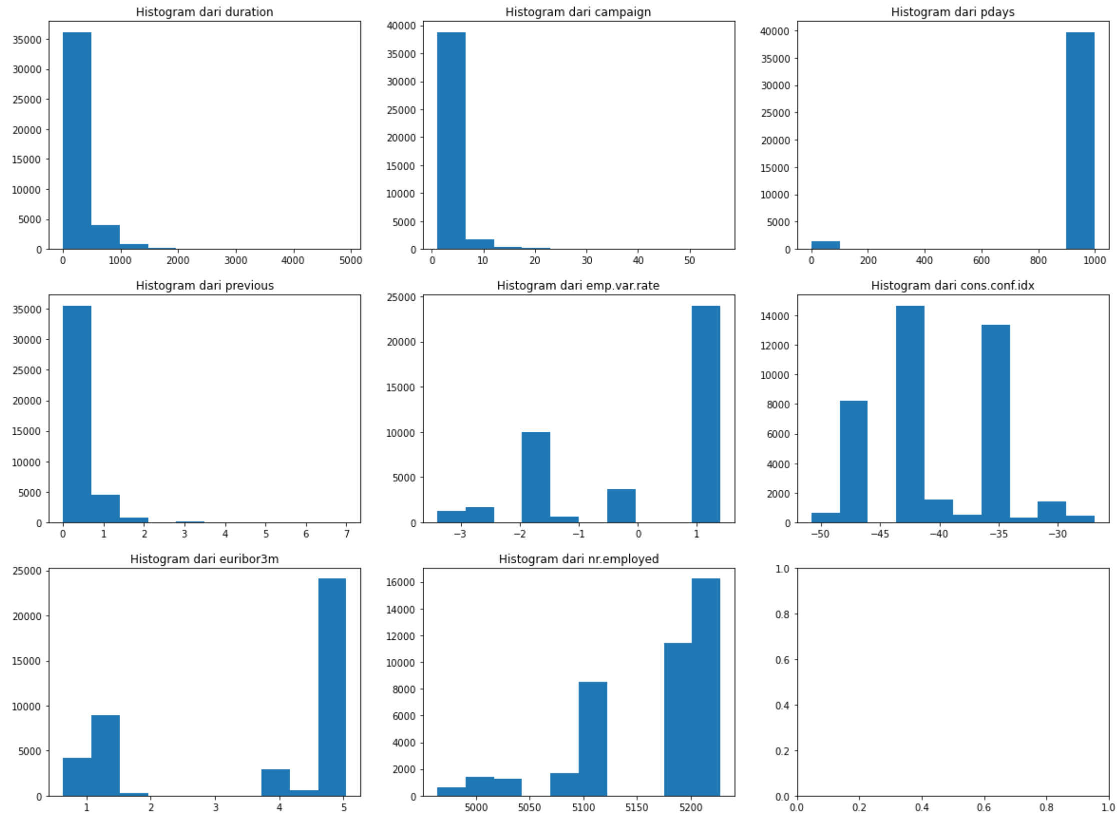


In [8]:
```
# Eksplor Kolom Kategorikal

categorical_cols = ['job','marital','education','credit','housing',
                    'loan','contact','month','poutcome']
fig, ax = plt.subplots(3,3, sharex=False, sharey=False, figsize=(25,20))
count = 0
for cat_col in categorical_cols:
    value_count = df[cat_col].value_counts()
    ax_x = count//3
    ax_y = count%3
    x_range = np.arange(0, len(value_count))
    ax[ax_x, ax_y].bar(x_range, value_count.values, tick_label=value_coun
t.index)
    ax[ax_x, ax_y].set_title(f"Bar plot dari {cat_col}")

    for i in ax[ax_x, ax_y].get_xticklabels():
        i.set_rotation(90)

    count+=1
plt.show()
```



In [9]:

```
# Eksplor Kolom Numerikal
num_cols = ['duration','campaign','pdays','previous','emp.var.rate',
            'cons.conf.idx','euribor3m','nr.employed']

fig, ax = plt.subplots(3,3, sharex=False, sharey=False, figsize=(20,15))
count = 0
for num_col in num_cols:
    ax_x = count//3
    ax_y = count%3

    ax[ax_x, ax_y].hist(df[num_col])
    ax[ax_x, ax_y].set_title(f"Histogram dari {num_col}")
    count+=1
plt.show()
```



In [10]:

```
# Mengganti value yes dengan 1 dan no dengan 0
df['subscribed'].replace({'yes':1, 'no':0}, inplace=True)
```

In [11]:

```
corr = df.corr()
print(corr['subscribed'].sort_values(axis=0, ascending=True))
```

```
nr.employed      -0.354678
pdays            -0.324914
euribor3m        -0.307771
emp.var.rate     -0.298334
cons.price.idx   -0.136211
campaign         -0.066357
age               0.030399
cons.conf.idx     0.054878
previous          0.230181
duration          0.405274
subscribed        1.000000
Name: subscribed, dtype: float64
```

In [12]:
```
# Drop features yang memiliki korelasi lebih sedikit dan tidak relevan de
ngan proses klasifikasi
df.drop(columns=['nr.employed','pdays','euribor3m','emp.var.rate',
    'cons.price.idx','day_of_week','cons.conf.idx','contact','month'],axi
s=0, inplace=True)
```

In [13]:
```
df
```

Out[13]:

	age	job	marital	education	credit	housing	loan	duration	cam
0	56	housemaid	married	basic.4y	no	no	no	261	
1	57	services	married	high.school	unknown	no	no	149	
2	37	services	married	high.school	no	yes	no	226	
3	40	admin.	married	basic.6y	no	no	no	151	
4	56	services	married	high.school	no	no	yes	307	
...	...	...	...	...	...	...	...	...	
41183	73	retired	married	professional.course	no	yes	no	334	
41184	46	blue-collar	married	professional.course	no	no	no	383	
41185	56	retired	married	university.degree	no	yes	no	189	
41186	44	technician	married	professional.course	no	no	no	442	
41187	74	retired	married	professional.course	no	yes	no	239	

41188 rows × 12 columns

In [14]:
```
encoder = LabelEncoder()
col = ['marital','credit','housing','loan']

for i in col:
    df[i] = encoder.fit_transform(df[i])
```

In [15]:
```
# Encoding
cat_features = ['job','marital','education','credit','housing','loan','po
utcome']
df = pd.get_dummies(df, columns=cat_features, drop_first=True)
df
```

Out[15]:

	age	duration	campaign	previous	subscribed	job_blue-collar	job_entrepreneur	job_ho
0	56	261	1	0	0	0	0	
1	57	149	1	0	0	0	0	
2	37	226	1	0	0	0	0	
3	40	151	1	0	0	0	0	
4	56	307	1	0	0	0	0	
...	...	...	...	...	...	...	...	
41183	73	334	1	0	1	0	0	
41184	46	383	1	0	0	1	0	
41185	56	189	2	0	0	0	0	
41186	44	442	1	0	1	0	0	
41187	74	239	3	1	0	0	0	

41188 rows × 34 columns

In [16]:
```
# Assign variable features dan label
X = df.drop(columns='subscribed', axis=1).values
y = df['subscribed'].values
```

In [17]:
```
# Splitting data scaling
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,
random_state=103)
```

In [18]:
```
ss = StandardScaler()
X_train = ss.fit_transform(X_train)
X_test = ss.fit_transform(X_test)
```

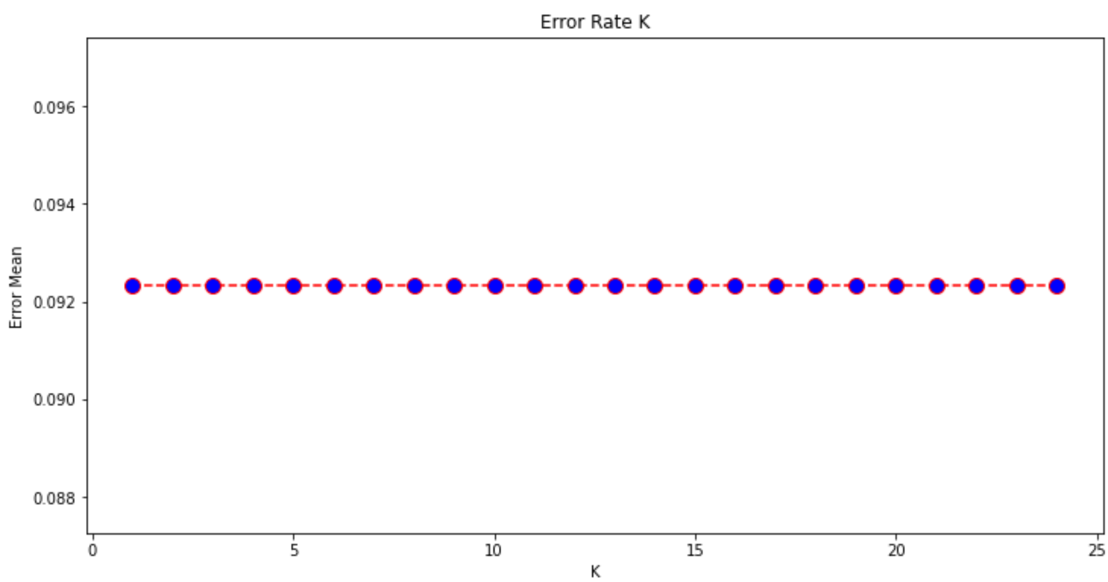
1. Logistik Regression

Logistik Regression memprediksi probabilitas sampel dalam satu klasifikasi versus klasifikasi lainnya. Nilai keluaran dalam logistik regression adalah klasifikasi bernomor.

In [19]:
```
# Logistik Regression
from sklearn.linear_model import LogisticRegression
model_lr = LogisticRegression()
model_lr.fit(X_train, y_train)
ypred1 = model_lr.predict(X_test)

print(metrics.classification_report(y_test, ypred1))
print("Akurasi : ",metrics.accuracy_score(y_test, ypred1))
print("Confusion Matrix :",'\n',metrics.confusion_matrix(y_test, ypred1))
```

```
              precision    recall  f1-score   support

           0       0.92      0.98      0.95     10969
           1       0.67      0.35      0.46      1388

    accuracy                           0.91     12357
   macro avg       0.80      0.66      0.70     12357
weighted avg       0.89      0.91      0.89     12357

Akurasi :  0.9076636724123979
Confusion Matrix :
 [[10731   238]
 [  903   485]]
```

In [20]:
```
error = []

for i in range (1,25):
    lr = LogisticRegression()
    lr.fit(X_train, y_train)
    pred = lr.predict(X_test)
    error.append(np.mean(pred != y_test))

plt.figure(figsize=(12,6));
plt.plot(range(1,25), error, color='red', linestyle='dashed', marker='o',
        markerfacecolor='blue', markersize=10);
plt.title('Error Rate K');
plt.xlabel('K');
plt.ylabel('Error Mean');
```



Dari plot tersebut dapat terlihat bahwa error cenderung stabil di 0.0921 pada setiap K.

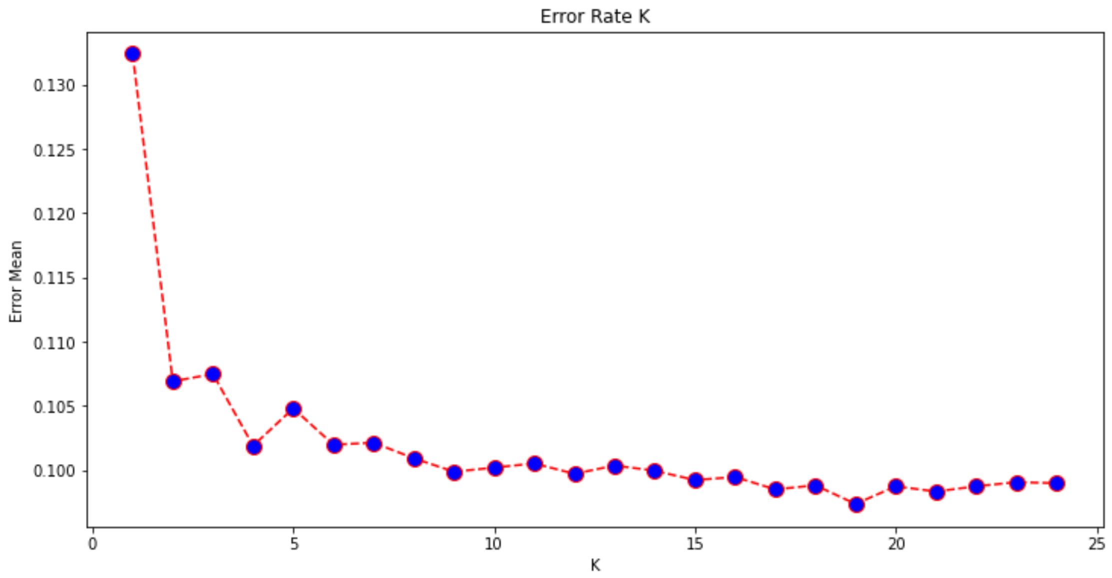
2. K-Nearest Neighbor (KNN)

KNN adalah algoritma non-parametric dan lazy learning algorithm. Non-parametric berarti tidak ada asumsi untuk distribusi data yang mendasarinya. Lazy algortihm berarti tidak memerlukan training data points untuk pembuatan model.

In [21]:
```
# K-Nearest Neighbor (KNN)
from sklearn.neighbors import KNeighborsClassifier
kNN = KNeighborsClassifier()
kNN.fit(X_train, y_train)
ypred2=kNN.predict(X_test)

print(metrics.classification_report(y_test, ypred2))
print("Akurasi : ", metrics.accuracy_score(y_test, ypred2))
print("Confusion Matrix :",'\n',metrics.confusion_matrix(y_test, ypred2))
```

```
              precision    recall  f1-score   support

           0       0.92      0.97      0.94     10969
           1       0.56      0.29      0.39      1388

    accuracy                           0.90     12357
   macro avg       0.74      0.63      0.66     12357
weighted avg       0.88      0.90      0.88     12357

Akurasi :  0.8952011005907583
Confusion Matrix :
 [[10654   315]
 [  980   408]]
```

In [22]:
```python
error = []

for i in range (1,25):
    knn = KNeighborsClassifier(n_neighbors=i)
    knn.fit(X_train, y_train)
    pred_i = knn.predict(X_test)
    error.append(np.mean(pred_i != y_test))

plt.figure(figsize=(12,6));
plt.plot(range(1,25), error, color='red', linestyle='dashed', marker='o',
         markerfacecolor='blue', markersize=10);
plt.title('Error Rate K');
plt.xlabel('K');
plt.ylabel('Error Mean');
```



Dari plot tersebut dapat terlihat bahwa error terkecil yang didapat adalah 0.03 pada K=19.

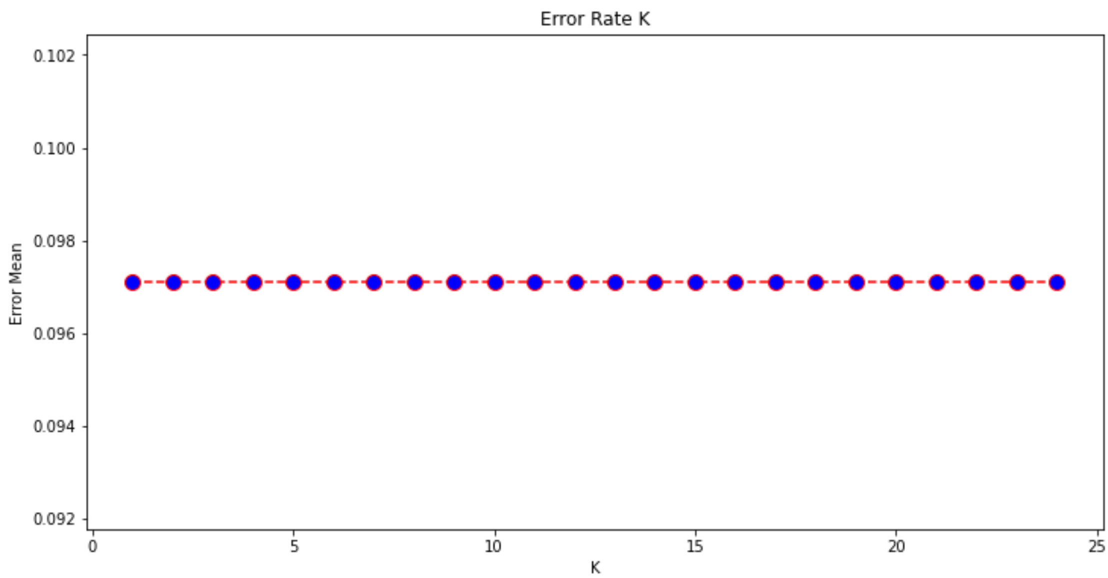
3. Support Vector Machines (SVM)

SVM menggunakan teknik yang disebut Kernel. Kernel mengambil low-dimensional input space dan mengubahnya menjadi ruang dengan dimensi lebih tinggi. SVM paling berguna dalam pemisahan masalah non-linier. Kernel membantu membuat klasifikasi lebih akurat.

In [23]:
```python
# Support Vector Machines (SVM)
from sklearn import svm
svm_model = svm.SVC()
svm_model.fit(X_train, y_train)
ypred3=svm_model.predict(X_test)

print(metrics.classification_report(y_test, ypred3))
print("Akurasi : ", metrics.accuracy_score(y_test, ypred3))
print("Confusion Matrix :",'\n',metrics.confusion_matrix(y_test, ypred3))
```

```
              precision    recall  f1-score   support

           0       0.91      0.98      0.95     10969
           1       0.68      0.26      0.37      1388

    accuracy                           0.90     12357
   macro avg       0.80      0.62      0.66     12357
weighted avg       0.89      0.90      0.88     12357

Akurasi :  0.902889050740471
Confusion Matrix :
 [[10801   168]
 [ 1032   356]]
```

In [24]:
```python
error = []

for i in range (1,25):
    svm_model = svm.SVC()
    svm_model.fit(X_train, y_train)
    ypred3=svm_model.predict(X_test)
    error.append(np.mean(ypred3 != y_test))

plt.figure(figsize=(12,6));
plt.plot(range(1,25), error, color='red', linestyle='dashed', marker='o',
        markerfacecolor='blue', markersize=10);
plt.title('Error Rate K');
plt.xlabel('K');
plt.ylabel('Error Mean');
```



Dari plot tersebut dapat terlihat bahwa error cenderung stabil di 0.097 pada setiap K.

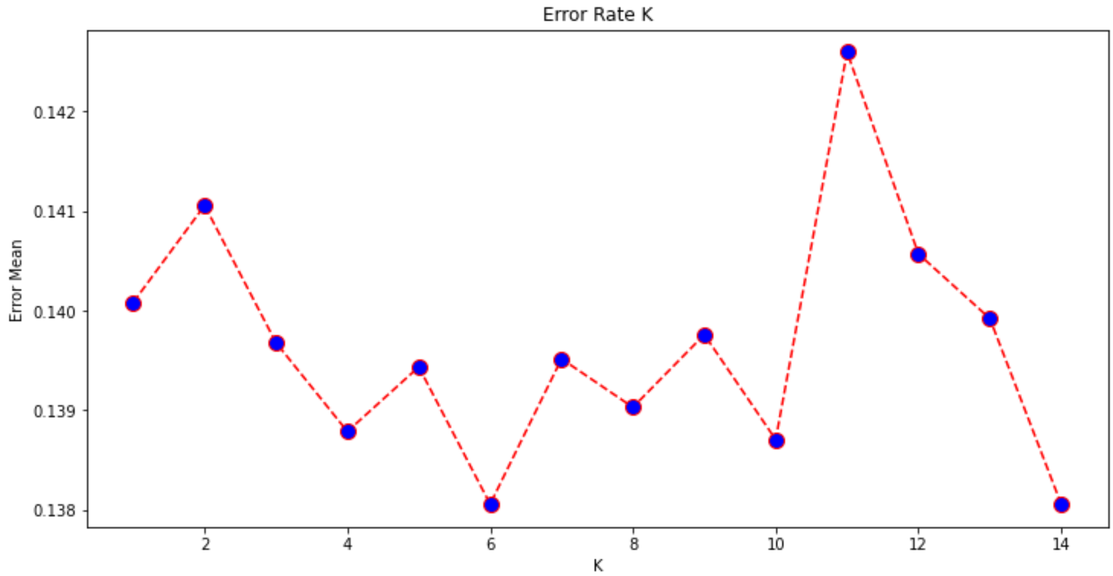
4. Decision Tree

Decision Tree adalah flowchart-like tree structure dimana internal node mewakili feature atau attribute, branch mewakili decision rule, dan setiap leaf node mewakili outcome. Node paling atas dalam pohon keputusan dikenal sebagai root node.

In [25]:
```
# Decision Tree
from sklearn import tree
from sklearn.tree import DecisionTreeClassifier
dt = tree.DecisionTreeClassifier()
dt.fit(X_train, y_train)
ypred4=dt.predict(X_test)

print(metrics.classification_report(y_test, ypred4))
print("Akurasi : ", metrics.accuracy_score(y_test, ypred4))
print("Confusion Matrix :",'\n',metrics.confusion_matrix(y_test, ypred4))
```

```
              precision    recall  f1-score   support

           0       0.93      0.92      0.92     10969
           1       0.40      0.44      0.41      1388

    accuracy                           0.86     12357
   macro avg       0.66      0.68      0.67     12357
weighted avg       0.87      0.86      0.86     12357

Akurasi :  0.8621024520514688
Confusion Matrix :
 [[10049   920]
 [  784   604]]
```

In [26]:
```
error = []

for i in range (1,15):
    dt = tree.DecisionTreeClassifier()
    dt.fit(X_train, y_train)
    ypred4=dt.predict(X_test)
    error.append(np.mean(ypred4 != y_test))

plt.figure(figsize=(12,6));
plt.plot(range(1,15), error, color='red', linestyle='dashed', marker='o',
        markerfacecolor='blue', markersize=10);
plt.title('Error Rate K');
plt.xlabel('K');
plt.ylabel('Error Mean');
```



Dari plot tersebut dapat terlihat bahwa error terkecil yang didapat adalah 0.138 pada K=6.

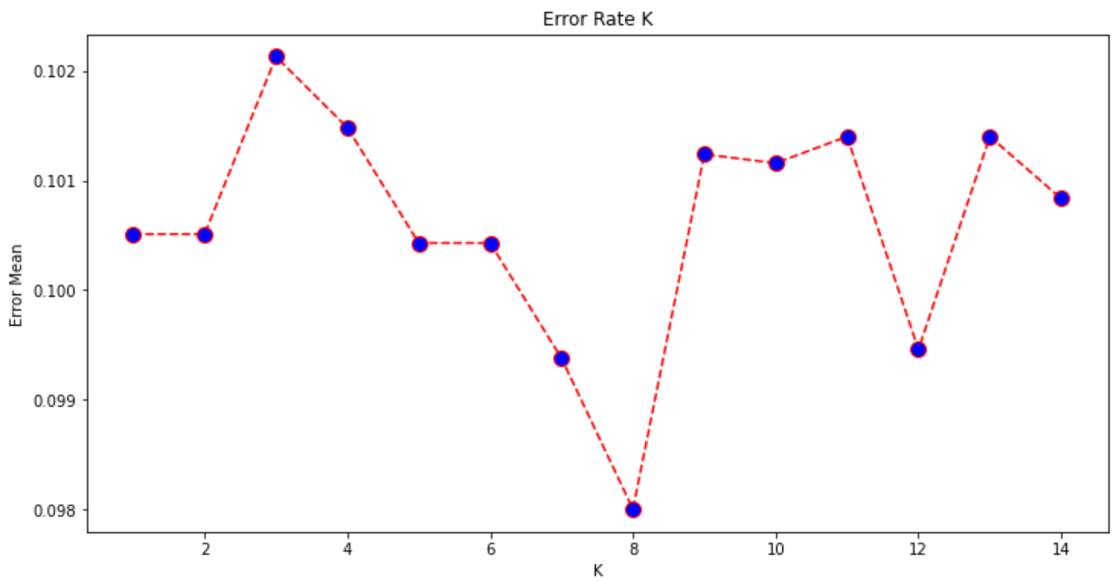
5. Random Forest

Random Forest adalah ensemble method dari decision trees yang dihasilkan pada dataset yang dipisahkan secara acak. Kumpulan decision tree classifier juga dikenal sebagai **forest**.

In [27]:
```
# Random Forest
from sklearn.ensemble import RandomForestClassifier
rf = RandomForestClassifier(n_estimators=100)
rf.fit(X_train, y_train)
ypred5=rf.predict(X_test)

print(metrics.classification_report(y_test, ypred5))
print("Akurasi : ", metrics.accuracy_score(y_test, ypred5))
print("Confusion Matrix :",'\n',metrics.confusion_matrix(y_test, ypred5))
```

```
              precision    recall  f1-score   support

           0       0.92      0.97      0.94     10969
           1       0.58      0.37      0.45      1388

    accuracy                           0.90     12357
   macro avg       0.75      0.67      0.70     12357
weighted avg       0.89      0.90      0.89     12357

Akurasi :  0.8995710933074371
Confusion Matrix :
 [[10606   363]
 [  878   510]]
```

In [28]:
```
error = []

for i in range (1,15):
    rf = RandomForestClassifier(n_estimators=100)
    rf.fit(X_train, y_train)
    ypred5=rf.predict(X_test)
    error.append(np.mean(ypred5 != y_test))

plt.figure(figsize=(12,6));
plt.plot(range(1,15), error, color='red', linestyle='dashed', marker='o',
        markerfacecolor='blue', markersize=10);
plt.title('Error Rate K');
plt.xlabel('K');
plt.ylabel('Error Mean');
```



Dari plot tersebut dapat terlihat bahwa error terkecil yang didapat adalah 0.098 pada K=8.

6. Naive Bayes

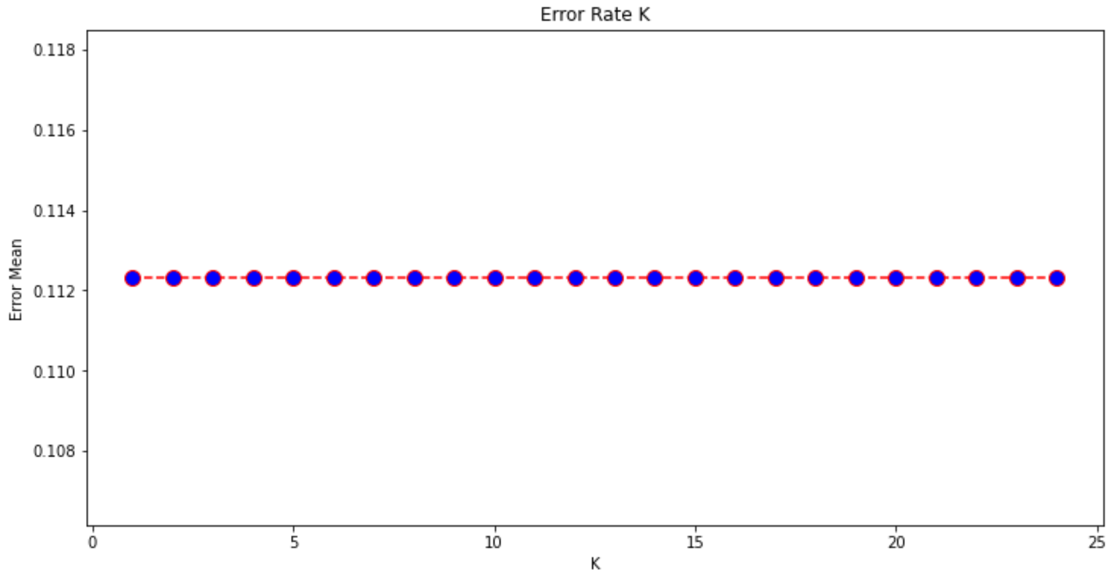
Naive Bayes adalah teknik klasifikasi statistik berdasarkan Bayes Theorem. Ini merupakan salah satu supervised learning algorithms yang paling sederhana. Naive Bayes Classifier adalah algoritma yang cepat, akurat, dan andal, memiliki akurasi dan kecepatan tinggi pada kumpulan data yang besar.

In [29]:

```
# Naive Bayes
from sklearn.naive_bayes import GaussianNB
nb = GaussianNB()
nb.fit(X_train, y_train)
ypred6=nb.predict(X_test)

print(metrics.classification_report(y_test, ypred6))
print("Akurasi : ", metrics.accuracy_score(y_test, ypred6))
print("Confusion Matrix :",'\n',metrics.confusion_matrix(y_test, ypred6))
```

```
              precision    recall  f1-score   support

           0       0.89      1.00      0.94     10969
           1       0.00      0.00      0.00      1388

    accuracy                           0.89     12357
   macro avg       0.44      0.50      0.47     12357
weighted avg       0.79      0.89      0.83     12357

Akurasi :  0.8876750020231448
Confusion Matrix :
 [[10969     0]
 [ 1388     0]]
```

In [30]:
```
error = []

for i in range (1,25):
    nb = GaussianNB()
    nb.fit(X_train, y_train)
    ypred6=nb.predict(X_test)
    error.append(np.mean(ypred6 != y_test))

plt.figure(figsize=(12,6));
plt.plot(range(1,25), error, color='red', linestyle='dashed', marker='o',
        markerfacecolor='blue', markersize=10);
plt.title('Error Rate K');
plt.xlabel('K');
plt.ylabel('Error Mean');
```



Dari plot tersebut dapat terlihat bahwa error cenderung stabil di 0.1121 pada setiap K.

Perbandingan Akurasi Beberapa Model

In [31]:
```
print("Logistic Regression : ", metrics.accuracy_score(y_test, ypred1))
print("K-Nearest Neighbor (KNN) : ", metrics.accuracy_score(y_test, ypred
2))
print("Support Vector Machines (SVM) : ", metrics.accuracy_score(y_test,
ypred3))
print("Decision Tree : ", metrics.accuracy_score(y_test, ypred4))
print("Random Forest : ", metrics.accuracy_score(y_test, ypred5))
print("Naive Bayes : ", metrics.accuracy_score(y_test, ypred6))
```

```
Logistic Regression :  0.9076636724123979
K-Nearest Neighbor (KNN) :  0.8952011005907583
Support Vector Machines (SVM) :  0.902889050740471
Decision Tree :  0.8619406004693696
Random Forest :  0.899166464352189
Naive Bayes :  0.8876750020231448
```

Kesimpulan

Berdasarkan hasil akurasi dari beberapa model seperti : Logistic Regression, K-Nearest Neighbor (KNN), Support Vector Machines (SVM), Decision Tree, Random Forest, dan Naive Bayes. Saya memilih **Logistic Regression**, karena memiliki tingkat akurasi yang paling tinggi di antara model yang lain yaitu sebesar **0.907** dan waktu yang dibutuhkan untuk runtime lebih cepat.

In [32]:
```
# Simpan hasil test dalam file .csv
predictions = pd.DataFrame(ypred1, columns=
                           ['predictions']).to_csv('H8_LR_Bank.csv')
```