In [1]:
```
#importing libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn as sklearn
from scipy import stats
```

In [2]:
```
#reading the data
data= pd.read_excel('iris.xls')
```

In [3]:
```
#performing EDA
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   SL              143 non-null    float64
 1   SW              144 non-null    float64
 2   PL              144 non-null    float64
 3   PW              150 non-null    float64
 4   Classification  150 non-null    object 
dtypes: float64(4), object(1)
memory usage: 6.0+ KB
```

In [4]:
```
data.shape
```

Out[4]:
```
(150, 5)
```

In [5]:
```
data.describe()
```

Out[5]:

	SL	SW	PL	PW
count	143.000000	144.000000	144.000000	150.000000
mean	5.855944	3.049306	3.756250	1.198667
std	0.828168	0.430644	1.761306	0.763161
min	4.300000	2.000000	1.000000	0.100000
25%	5.100000	2.800000	1.600000	0.300000
50%	5.800000	3.000000	4.350000	1.300000
75%	6.400000	3.300000	5.100000	1.800000
max	7.900000	4.400000	6.900000	2.500000

In [6]:
```
#checking for missing values
data.isna().sum()
```

Out[6]:
```
SL                7
SW                6
PL                6
PW                0
Classification    0
dtype: int64
```

In [7]:
```
data.head()
```

Out[7]:

	SL	SW	PL	PW	Classification
0	5.1	3.5	1.4	0.2	Iris-setosa
1	4.9	3.0	1.4	0.2	Iris-setosa
2	NaN	3.2	1.3	0.2	Iris-setosa
3	4.6	3.1	1.5	0.2	Iris-setosa
4	5.0	3.6	1.4	0.2	Iris-setosa

In [8]:
```
data.columns
```

Out[8]:
```
Index(['SL', 'SW', 'PL', 'PW', 'Classification'], dtype='object')
```

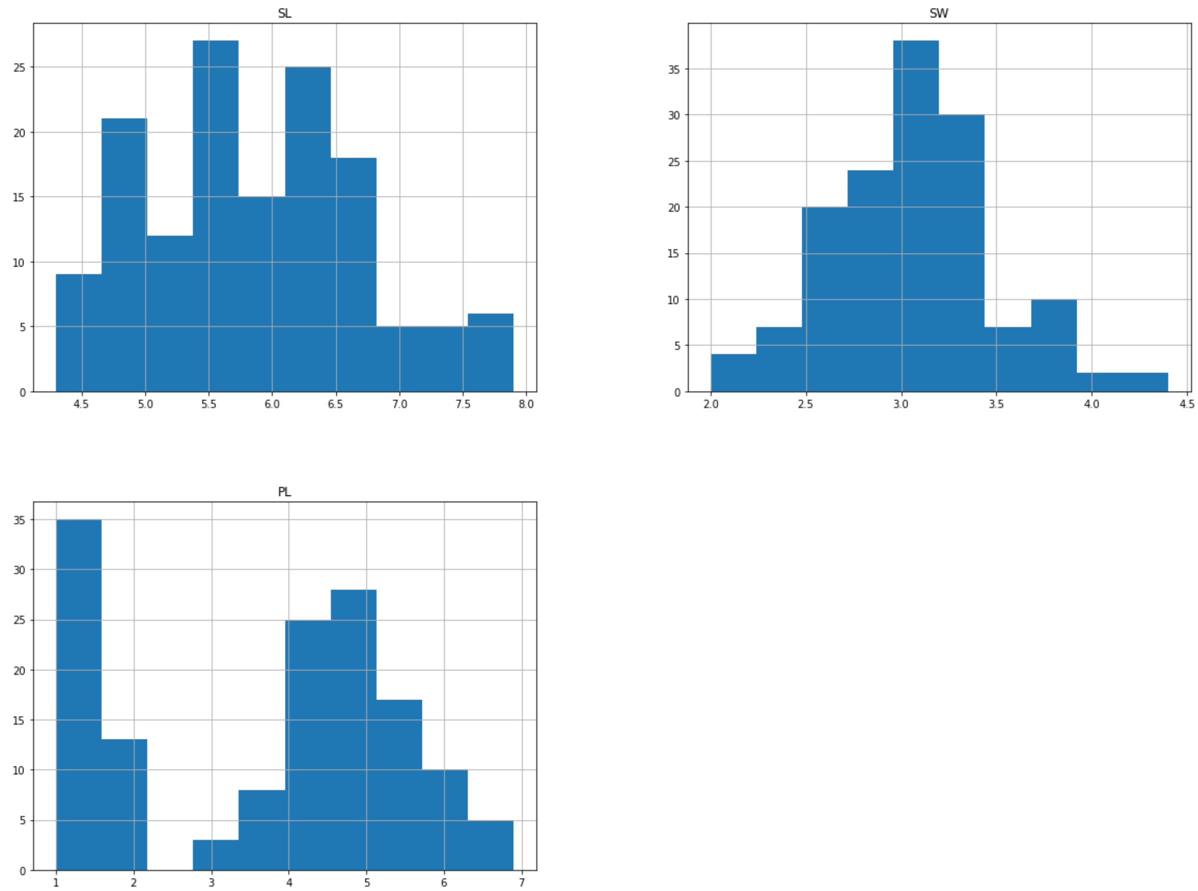
In [9]:
```
#handling missing values
num_cols=data[['SL', 'SW', 'PL']]
```

In [10]:
```
num_cols.isna().sum()
```

Out[10]:
```
SL    7
SW    6
PL    6
dtype: int64
```

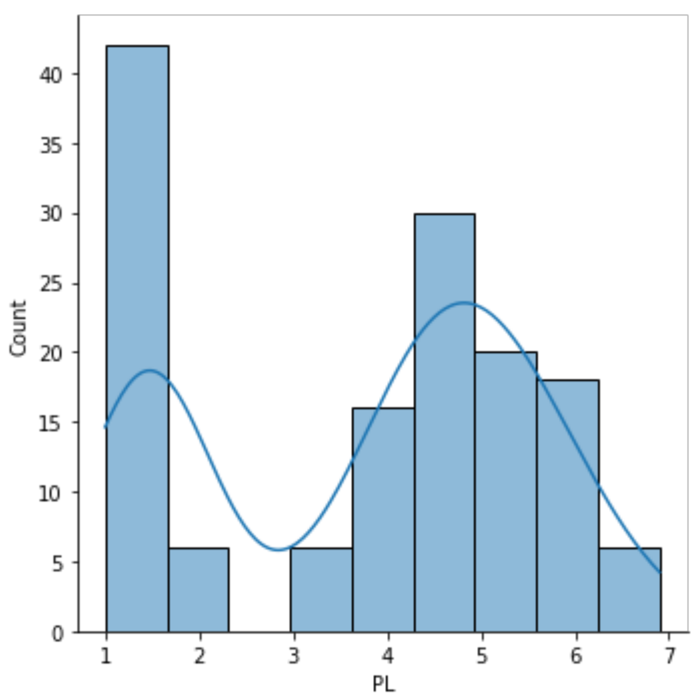
In [11]:
```
#missing values of normal distributed data can be filled by mean or median
#skewed data can be filled by median
#to find if data normal or skewed we plot it

freqgraph=num_cols.select_dtypes(include=['float'])
freqgraph.hist(figsize=(20,15))
plt.show()
```



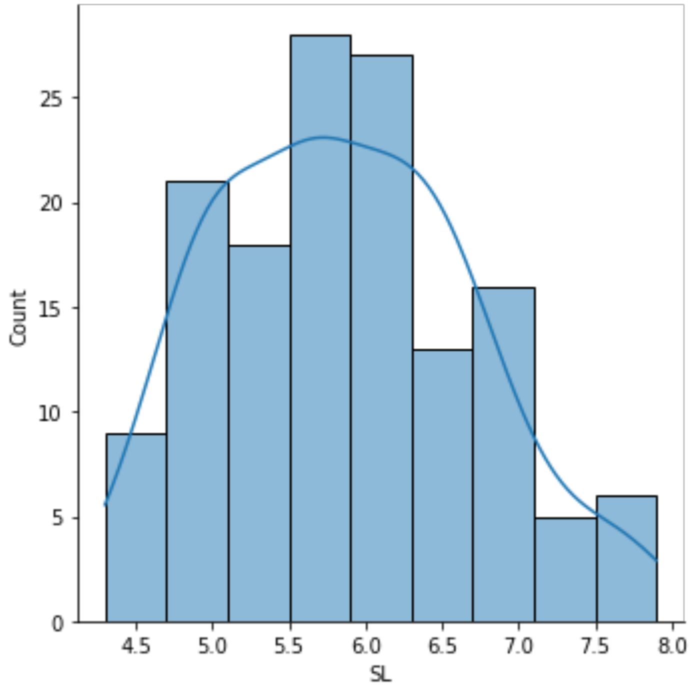
In [12]:
```
#ploting distplot
sns.displot(data.PL, kde=True)
```

Out[12]: <seaborn.axisgrid.FacetGrid at 0x7f4a95df7be0>



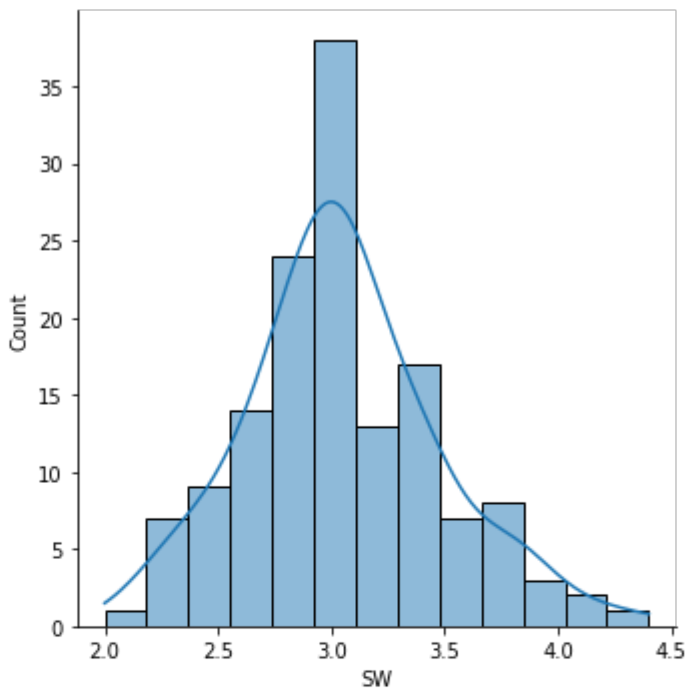
In [13]:
```
sns.displot(data.SL, kde=True)
```

Out[13]: <seaborn.axisgrid.FacetGrid at 0x7f4a933b1b20>



In [14]:
```
sns.displot(data.SW, kde=True)
```

Out[14]: <seaborn.axisgrid.FacetGrid at 0x7f4a95e4d1c0>



In [15]:
```
#filling missing values of SL and PL by median
for col in ['SL','PL']:
   data[col]=data[col].fillna(data[col].median())
```

In [16]:
```
#filling missing values of SW by mean
data['SW']=data['SW'].fillna(data['SW'].mean())
```

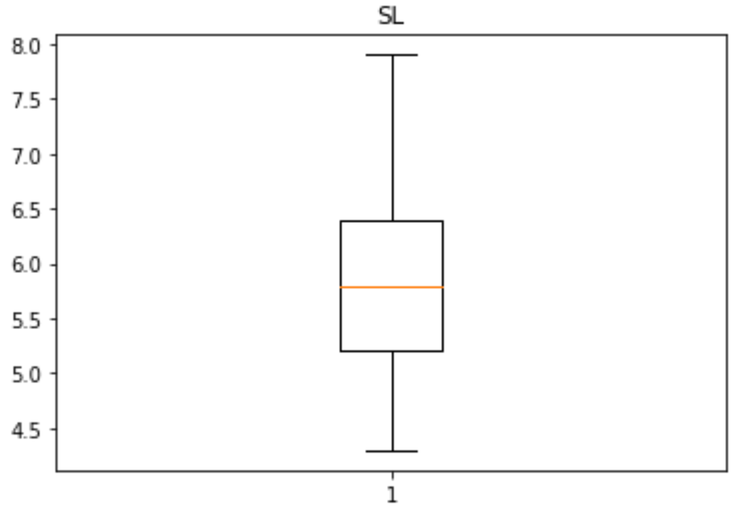
In [17]:
```
#missing values are handled
data.isna().sum()
```

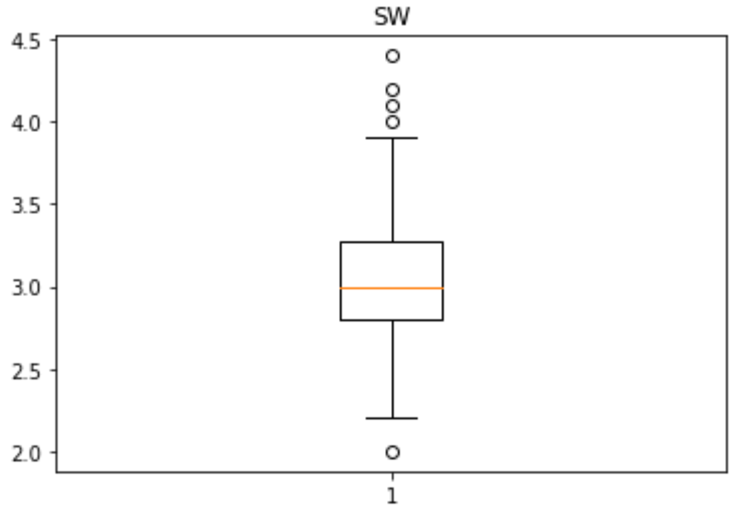
Out[17]:
```
SL                0
SW                0
PL                0
PW                0
Classification    0
dtype: int64
```

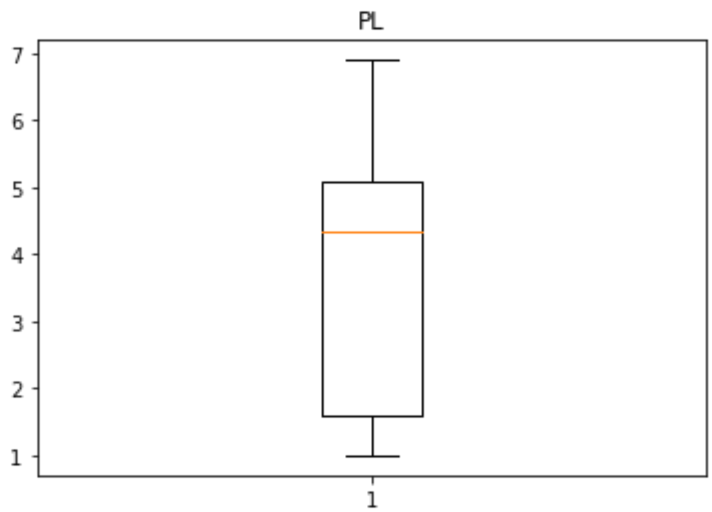
In [18]:
```
#performing shapiro test
from scipy.stats import shapiro
# normality test
stat, p = shapiro(data.PL)
print('Statistics=%.3f, p=%.3f' % (stat, p))
# interpret results
alpha = 0.05
if (p > alpha):
    print('Sample looks Gaussian (fail to reject H0)')
else:
    print('Sample does not look Gaussian (reject H0)')
```

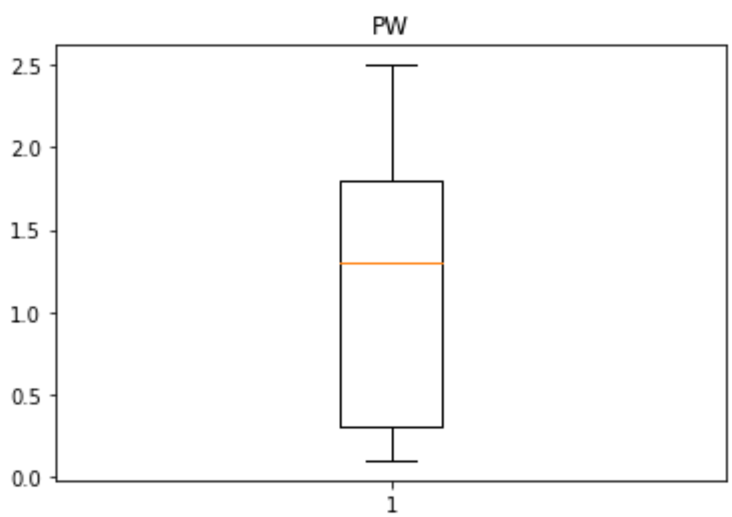
```
Statistics=0.880, p=0.000
Sample does not look Gaussian (reject H0)
```

In [19]:
```
#checking for outliners
#ploting boxplot to see outliners
for i in ['SL', 'SW', 'PL', 'PW']:
       plt.figure()
       plt.boxplot(data[i])
       plt.title(i)
```









In [20]:
```
#finding Q1,Q2,Q3
Q1=np.percentile(data['SW'],25,interpolation='midpoint')
Q2=np.percentile(data['SW'],50,interpolation='midpoint')
Q3=np.percentile(data['SW'],75,interpolation='midpoint')
```

```
<ipython-input-20-f234740ad858>:2: DeprecationWarning: the `interpolation=` argumen
t to percentile was renamed to `method=`, which has additional options.
Users of the modes 'nearest', 'lower', 'higher', or 'midpoint' are encouraged to re
view the method they. (Deprecated NumPy 1.22)
  Q1=np.percentile(data['SW'],25,interpolation='midpoint')
<ipython-input-20-f234740ad858>:3: DeprecationWarning: the `interpolation=` argumen
t to percentile was renamed to `method=`, which has additional options.
Users of the modes 'nearest', 'lower', 'higher', or 'midpoint' are encouraged to re
view the method they. (Deprecated NumPy 1.22)
  Q2=np.percentile(data['SW'],50,interpolation='midpoint')
<ipython-input-20-f234740ad858>:4: DeprecationWarning: the `interpolation=` argumen
t to percentile was renamed to `method=`, which has additional options.
Users of the modes 'nearest', 'lower', 'higher', or 'midpoint' are encouraged to re
view the method they. (Deprecated NumPy 1.22)
  Q3=np.percentile(data['SW'],75,interpolation='midpoint')
```

In [21]:

```
print(Q1)
print(Q2)
print(Q3)
```

```
2.8
3.0
3.25
```

In [22]:

```
data['SW'].median()
```

Out[22]:

```
3.0
```

In [23]:

```
#finding IQR
IQR=stats.iqr(data.SW,interpolation="midpoint")
IQR
```

Out[23]:

```
0.4500000000000002
```

In [24]:

```
#finding min and max limit
min_limit=Q1-1.5*IQR
max_limit=Q3+1.5*IQR
min_limit,max_limit
```

Out[24]:

```
(2.1249999999999996, 3.9250000000000003)
```

In [25]:

```
#finding points greater than max limit as outliners
data.loc[data.SW>max_limit]
```

Out[25]:

	SL	SW	PL	PW	Classification
14	5.8	4.0	1.2	0.2	Iris-setosa
15	5.7	4.4	1.5	0.4	Iris-setosa
32	5.2	4.1	1.5	0.1	Iris-setosa
33	5.5	4.2	1.4	0.2	Iris-setosa

In [26]:
```
#finding points less than min limit as outliners
data.loc[data.SW<min_limit]
```

Out[26]:

	SL	SW	PL	PW	Classification
60	5.0	2.0	3.5	1.0	Iris-versicolor

In [27]:
```
#replacing the outliners by median
data.loc[data['SW']>max_limit,'SW']=np.median(data.SW)
```

In [28]:
```
#replacing the outliners by median
data.loc[data['SW']<min_limit,'SW']=np.median(data.SW)
```

In [29]:
```
data.loc[data.SW>max_limit]
```

Out[29]:

SL	SW	PL	PW	Classification

In [30]:
```
data.loc[data.SW>max_limit]
```

Out[30]:

SL	SW	PL	PW	Classification

In [31]:
```
data['Classification'].nunique()
```

Out[31]: 3

In [32]:
```
#classification
```

In [33]:
```
data.head()
```

Out[33]:

	SL	SW	PL	PW	Classification
0	5.1	3.5	1.4	0.2	Iris-setosa
1	4.9	3.0	1.4	0.2	Iris-setosa
2	5.8	3.2	1.3	0.2	Iris-setosa
3	4.6	3.1	1.5	0.2	Iris-setosa
4	5.0	3.6	1.4	0.2	Iris-setosa

In [34]:
```
#spliting data as x and y
y=data['Classification']
x=data.drop(['Classification'],axis=1)
```

In [34]:
```
```

In [35]:
```
#splitting as test and training sets
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2, random_state=42)
```

In [36]:
```
#performing one hot encoding
from sklearn.preprocessing import OneHotEncoder
enc = OneHotEncoder(handle_unknown = 'ignore')
enc.fit(x_train)
```

Out[36]:
```
▾ OneHotEncoder
OneHotEncoder(handle_unknown='ignore')
```

In [37]:
```
enc.transform(x_train).toarray()
```

Out[37]:
```
array([[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.]])
```

In [38]:
```
enc.transform(x_test).toarray()
```

Out[38]:
```
array([[0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 1., 0., 0.],
       ...,
       [0., 0., 0., ..., 1., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.]])
```

In [39]:
```
#performing scaling
from sklearn.preprocessing import StandardScaler
sc=StandardScaler()
x_train=sc.fit_transform(x_train)
x_test=sc.fit_transform(x_test)
```

In [40]:
```
#performing logistic regression on data
from sklearn.linear_model import LogisticRegression
clf=LogisticRegression()
model=clf.fit(x_train,y_train)
```

In [41]:
```
#prediction on x_test
y_pred=model.predict(x_test)
```

In [42]:
```
#evaluating our model
from sklearn.metrics import confusion_matrix ,accuracy_score,precision_score,recall
print('Accuracy=',accuracy_score(y_test,y_pred))
print('Precision=',precision_score(y_test,y_pred,average='macro'))
print('Recall=',recall_score(y_test,y_pred,average='macro'))
print('F1=',f1_score(y_test,y_pred,average= 'macro'))
```

```
Accuracy= 0.9666666666666667
Precision= 0.9666666666666667
Recall= 0.9696969696969697
F1= 0.9665831244778613
```

In [43]:
```
#printing confusion matrix
confusion_matrix(y_test,y_pred)
```

Out[43]:
```
array([[10,  0,  0],
       [ 0,  9,  0],
       [ 0,  1, 10]])
```

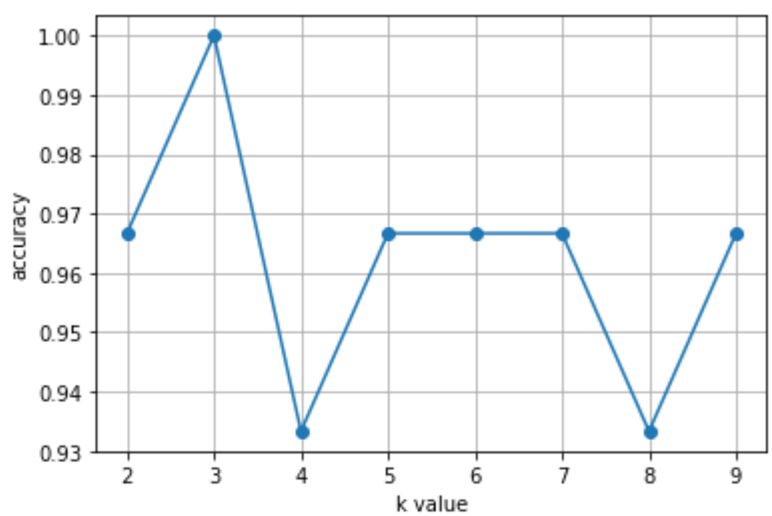
In [44]:
```
#KNN
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2, random_state=42)
sc=StandardScaler()
x_train=sc.fit_transform(x_train)
x_test=sc.fit_transform(x_test)
from sklearn.neighbors import KNeighborsClassifier
metric_k=[]#creating empty list for putting accuracy values of different k values
neighbors=np.arange(2,10)#creating array with values 3 to 15

for k in neighbors:#3 to 15 taken by k
       classifier=KNeighborsClassifier(n_neighbors=k,metric='minkowski',p=2)#instan
       model=classifier.fit(x_train,y_train)#model created
       y_pred=model.predict(x_test)
       acc =accuracy_score(y_test,y_pred)
       metric_k.append(acc)#given accuracy to empty list
```

In [45]:
```
metric_k#maximum value in this ,that k value taken
```

Out[45]:
```
[0.9666666666666667,
 1.0,
 0.9333333333333333,
 0.9666666666666667,
 0.9666666666666667,
 0.9666666666666667,
 0.9333333333333333,
 0.9666666666666667]
```

In [46]:
```
#ploting the list metric_k
plt.plot(neighbors,metric_k,'o-')
plt.xlabel('k value')
plt.ylabel('accuracy')
plt.grid()
```



In [47]:
```
classifier=KNeighborsClassifier(3,metric='minkowski',p=2)#instance called classifie
model=classifier.fit(x_train,y_train)#model created
y_pred=model.predict(x_test)#predicting the model
print('Accuracy=',accuracy_score(y_test,y_pred))
print('Precision=',precision_score(y_test,y_pred,average='macro'))
print('Recall=',recall_score(y_test,y_pred,average='macro'))
print('F1=',f1_score(y_test,y_pred,average='macro'))
```

```
Accuracy= 1.0
Precision= 1.0
Recall= 1.0
F1= 1.0
```

In [48]:
```
#printing confusion matrix
confusion_matrix(y_test,y_pred)
```

Out[48]:
```
array([[10,  0,  0],
       [ 0,  9,  0],
       [ 0,  0, 11]])
```

In [49]:
```
data.head()
```

Out[49]:

	SL	SW	PL	PW	Classification
0	5.1	3.5	1.4	0.2	Iris-setosa
1	4.9	3.0	1.4	0.2	Iris-setosa
2	5.8	3.2	1.3	0.2	Iris-setosa
3	4.6	3.1	1.5	0.2	Iris-setosa
4	5.0	3.6	1.4	0.2	Iris-setosa

In [50]:
```
#SVM DT RF
```

In [51]:
```
y=data['Classification']
x=data.drop(['Classification'],axis=1)
```

In [52]:
```
#spliting as test and train set
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2, random_state=42)
```

In [53]:
```
#importing svm from sklearn
from sklearn.svm import SVC
svmclf=SVC(kernel='linear')#instance with kernal as linear
svmclf.fit(x_train,y_train)
```

Out[53]:
```
▾ SVC
SVC(kernel='linear')
```

In [54]:
```
y_pred_svm=svmclf.predict(x_test)#predicting using model
```

In [55]:
```
from sklearn.metrics import accuracy_score,confusion_matrix
```

In [56]:
```
print(accuracy_score(y_test,y_pred_svm))#printing accuracy
```

```
1.0
```

In [57]:
```
print(confusion_matrix(y_test,y_pred_svm))#printing confusion matrix
```

```
[[10  0  0]
 [ 0  9  0]
 [ 0  0 11]]
```

In [58]:
```
from sklearn.svm import SVC
svmclf=SVC(kernel='rbf')#instance with kernal as rfb
svmclf.fit(x_train,y_train)
```

Out[58]:
```
▾ SVC
SVC()
```

In [59]:
```
y_pred_svm=svmclf.predict(x_test)#prediction on x_test
```

In [60]:
```
print(accuracy_score(y_test,y_pred_svm))#printing accuracy
```

```
1.0
```

In [61]:
```
from sklearn.svm import SVC
svmclf=SVC(kernel='poly')#instance with kernal as poly
svmclf.fit(x_train,y_train)
```

Out[61]:
```
▾         SVC
SVC(kernel='poly')
```

In [62]:
```
y_pred_svm=svmclf.predict(x_test)#prediction on x_test
```

In [63]:
```
print(accuracy_score(y_test,y_pred_svm))#printing accuracy
```

```
0.9666666666666667
```

In [64]:
```
#decision tree
from sklearn.tree import DecisionTreeClassifier
dt_clf=DecisionTreeClassifier(random_state=42)#instance variable with random state
dt_clf.fit(x_train,y_train)
```

Out[64]:
```
▾         DecisionTreeClassifier
DecisionTreeClassifier(random_state=42)
```

In [65]:
```
y_pred_dt=dt_clf.predict(x_test)#prediction on x_test
```

In [66]:
```
print(accuracy_score(y_test,y_pred_dt))#printing accuracy
```

```
1.0
```

In [67]:
```
print(confusion_matrix(y_test,y_pred_dt))#printing confusion matrix
```

```
[[10  0  0]
 [ 0  9  0]
 [ 0  0 11]]
```

In [68]:
```
#Random Forest
from sklearn.ensemble  import RandomForestClassifier
rf_clf=RandomForestClassifier(n_estimators=50)#instance variable with n_estimators=
rf_clf.fit(x_train,y_train)
```

Out[68]:
```
▾         RandomForestClassifier

RandomForestClassifier(n_estimators=50)
```

In [69]:
```
y_pred_rf=rf_clf.predict(x_test)#prediction on x_test
```

In [70]:
```
print(accuracy_score(y_test,y_pred_rf))#printing accuracy
```

```
1.0
```

In [71]:
```
print(confusion_matrix(y_test,y_pred_rf))#printing confusion matrix
```

```
[[10  0  0]
 [ 0  9  0]
 [ 0  0 11]]
```

In [72]:
```
#logistic regression had Accuracy= 0.9666666666666667
#knn when k_value=3 had accuracy=1.0
#svm(linear and rfg)had accuracy=1.0
#svm(poly) had accuracy as 0.9666666666666667
#Decision tree and random forest had accuracy=1.0
```

In [73]:
```
#so KNN,SVM(linear,rfg), DT, RF are good classifiers
```