1 Basic Preprocessing

In [1]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
import warnings
warnings.filterwarnings("ignore")
from sklearn.model_selection import GridSearchCV
from scipy.stats import randint as sp_randint
from sklearn.model_selection import RandomizedSearchCV
import math
from sklearn.metrics import confusion_matrix
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import plot_confusion_matrix
from sklearn.metrics import classification_report
from sklearn.linear_model import LogisticRegression
np.random.seed(42)
```

In [2]:
```
column = ['Sepal_length', 'Sepal_width', 'Petal_length', 'Petal_width','class'
]
data = pd.read_csv('iris.data',names=column)
```

In [3]:
```
data.tail(3)
```

Out[3]:

	Sepal_length	Sepal_width	Petal_length	Petal_width	class
147	6.5	3.0	5.2	2.0	Iris-virginica
148	6.2	3.4	5.4	2.3	Iris-virginica
149	5.9	3.0	5.1	1.8	Iris-virginica

1.1 NUMBER OF DATAPOINTS AND NUMBER OF FEATURES

In [13]:
```
print('='*80)
print("Number of data points in data=", data.shape)
print('-'*80)
print("The attributes(columns or features) of data =\n", data.columns.values)
print('='*80)
```

```
================================================================================
===
Number of data points in data= (150, 5)
--------------------------------------------------------------------------------
---
The attributes(columns or features) of data =
 ['Sepal_length' 'Sepal_width' 'Petal_length' 'Petal_width' 'class']
================================================================================
===
```

1.2 UNIQUE LABELS IN DEPENDENT VARIABLE THAT Yi

In [14]:
```
print('='*90)
print("Number of unique labels in class=",data['class'].unique())
print('='*90)
```

```
================================================================================
=============
Number of unique labels in class= ['Iris-setosa' 'Iris-versicolor' 'Iris-virg
inica']
================================================================================
=============
```

1.3 NULL VALUES BASIC STATISTICS OF FEATURES

In [15]:
```
data.isnull().sum()
```

Out[15]:
```
Sepal_length    0
Sepal_width     0
Petal_length    0
Petal_width     0
class           0
dtype: int64
```

In [16]:
```
data.describe()
```

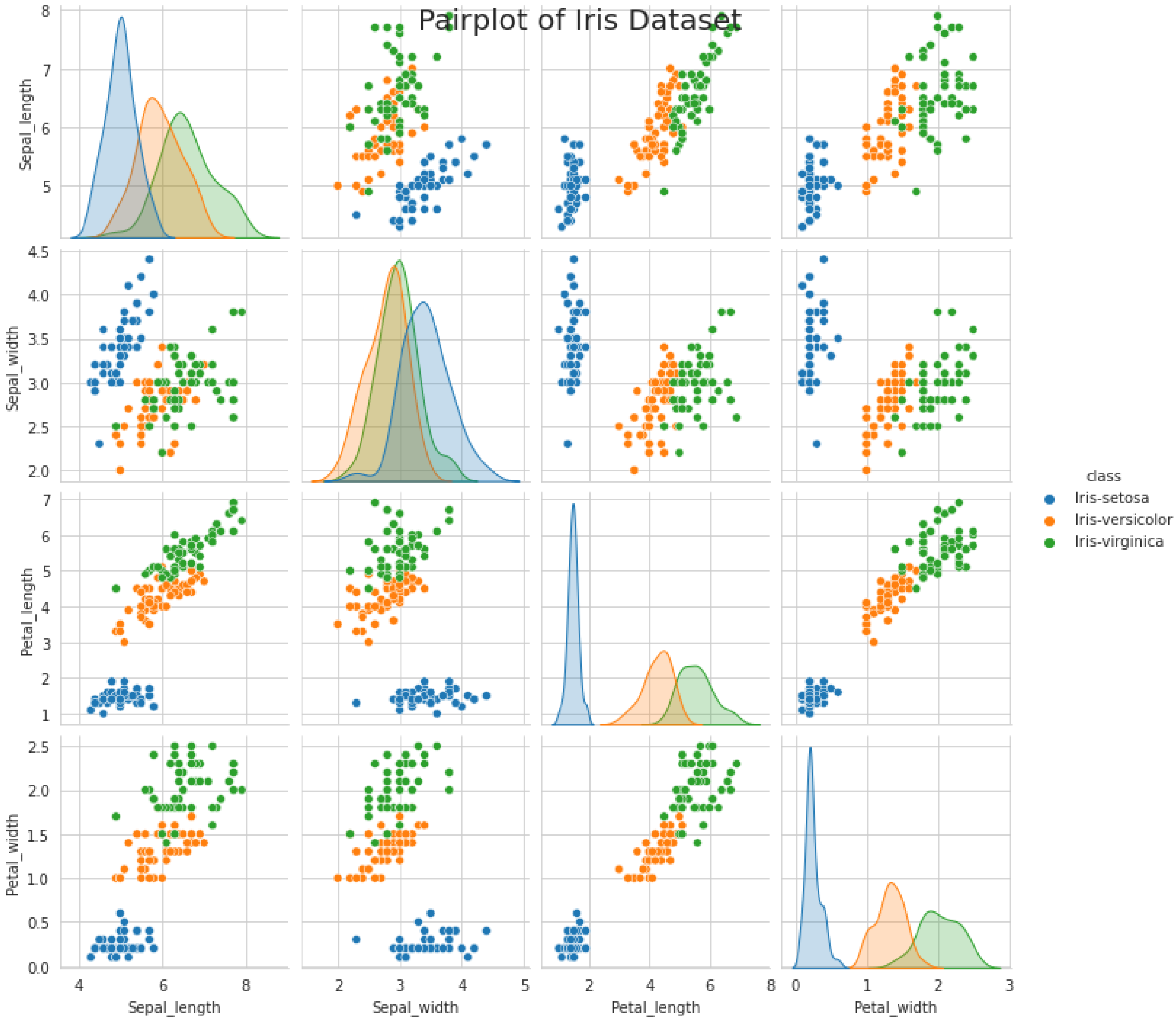
Out[16]:

	Sepal_length	Sepal_width	Petal_length	Petal_width
count	150.000000	150.000000	150.000000	150.000000
mean	5.843333	3.054000	3.758667	1.198667
std	0.828066	0.433594	1.764420	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

2 DATA VISUALIZATION AND EXPLOLATORY DATA ANALYSIS

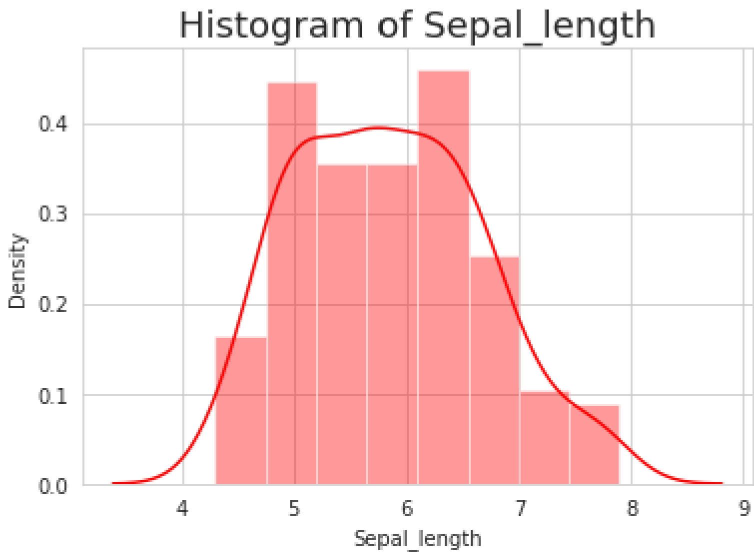
2.1 PAIRPLOT OF IRIS DATASET

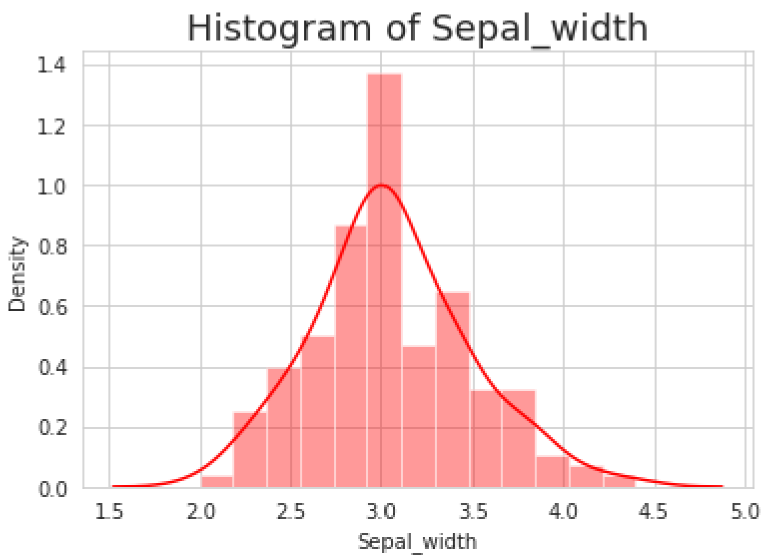
In [37]:
```
sns.set_style("whitegrid")
ax=sns.pairplot(data, hue="class")
ax.fig.suptitle("Pairplot of Iris Dataset ",size=20)
plt.show()
```

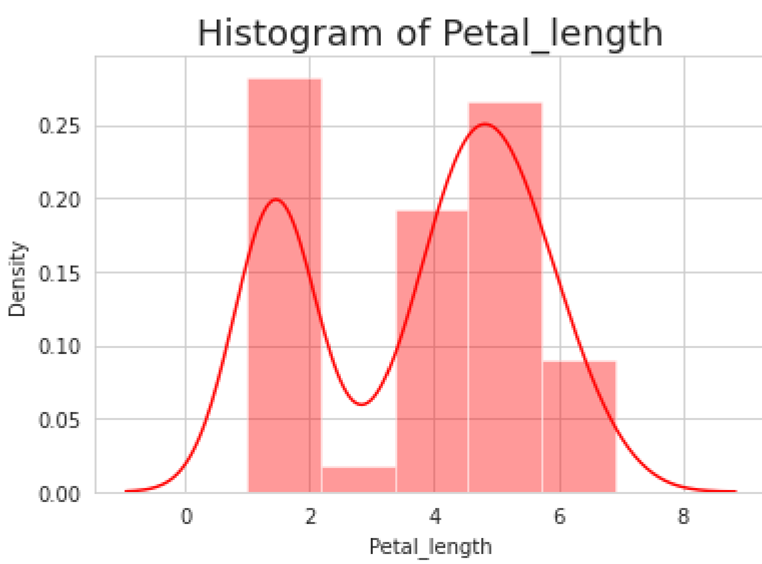


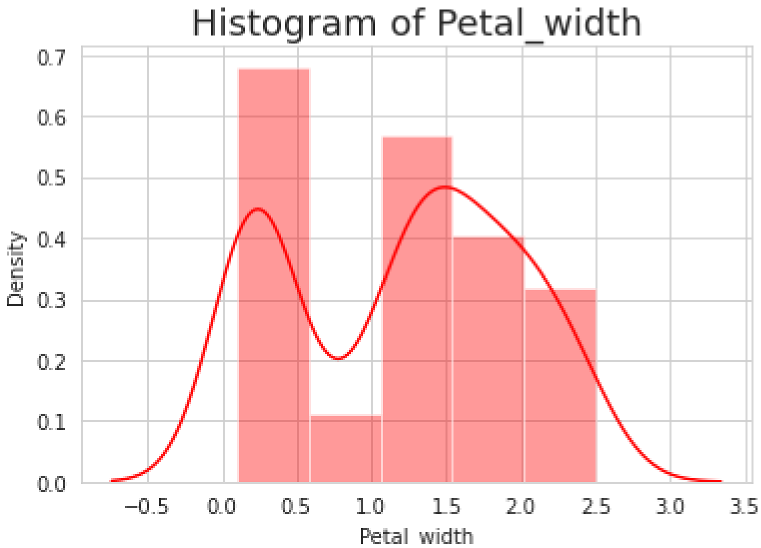
2.2 HISTOGRAM OF EVERY FEATURE

In [65]:
```
col_list=['Sepal_length', 'Sepal_width', 'Petal_length', 'Petal_width']
for i in col_list:
    plt.figure(figsize=(6,4))
    sns.set_style("whitegrid")
    sns.distplot(a=data[i],color="r")
    plt.title("Histogram of {}".format(i),fontsize=18)
```


Histogram of Sepal_length
Density
0.0
0.1
0.2
0.3
0.4
4
5
6
7
8
9
Sepal_length

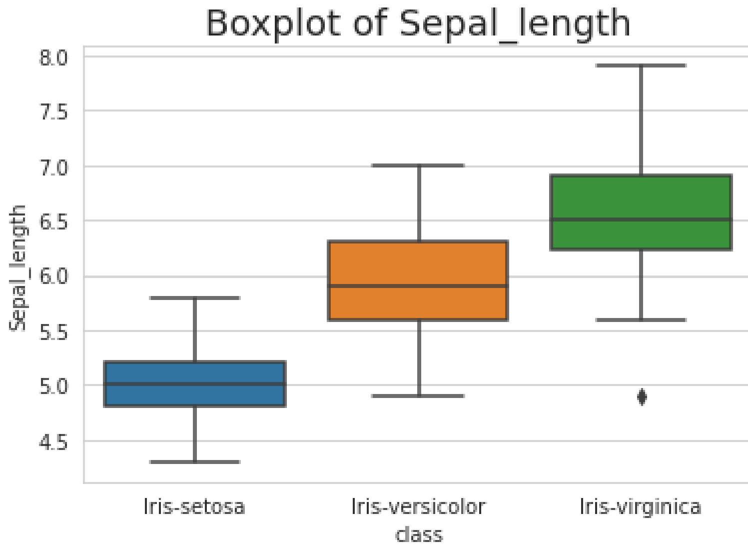

Histogram of Sepal_width
Density
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
Sepal_width

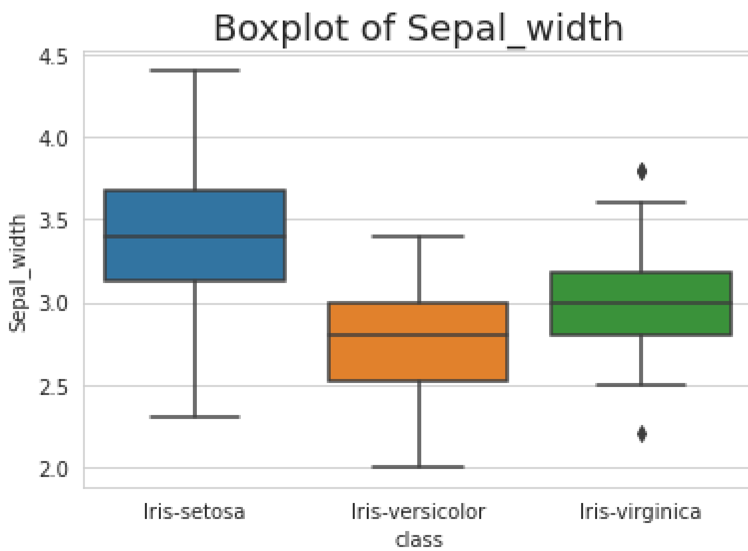

Histogram of Petal_length
Density
0.00
0.05
0.10
0.15
0.20
0.25
0
2
4
6
8
Petal_length

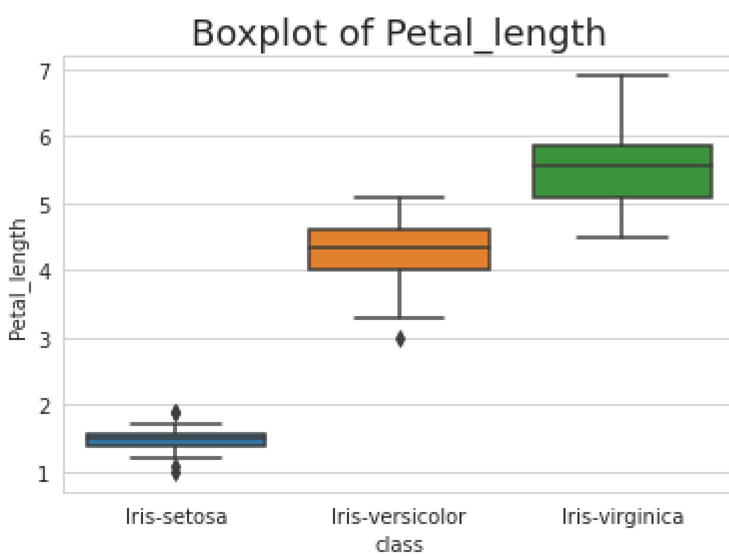

Histogram of Petal_width
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
Density
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
Petal_width

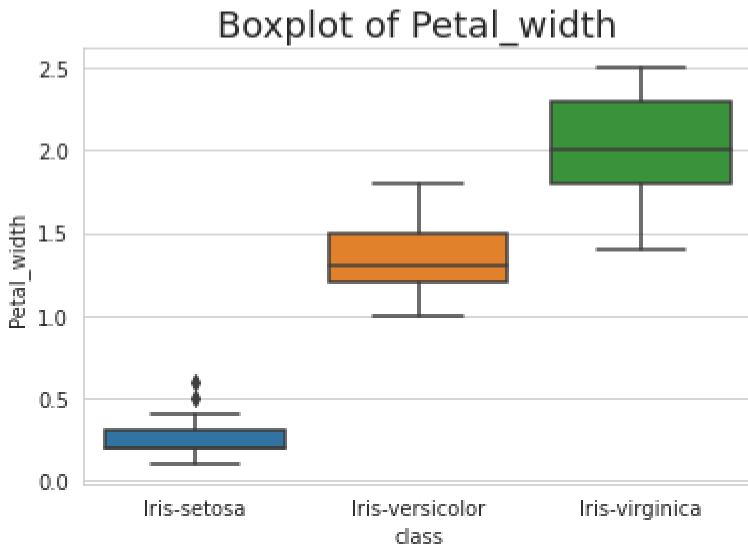
2.3 BOX PLOT

In [71]:
```
for i in col_list:
    plt.figure(figsize=(6,4))
    sns.set_style("whitegrid")
    sns.boxplot(x='class',y=i,data=data)
    plt.title("Boxplot of {}".format(i),fontsize=18)
```


Boxplot of Sepal_length
8.0
7.5
7.0
6.5
6.0
5.5
5.0
4.5
Sepal_length
Iris-setosa
Iris-versicolor
Iris-virginica
class


Boxplot of Sepal_width
4.5
4.0
3.5
3.0
2.5
2.0
Sepal_width
Iris-setosa
Iris-versicolor
Iris-virginica
class


Boxplot of Petal_length
7
6
5
4
3
2
1
Petal_length
Iris-setosa
Iris-versicolor
Iris-virginica
class



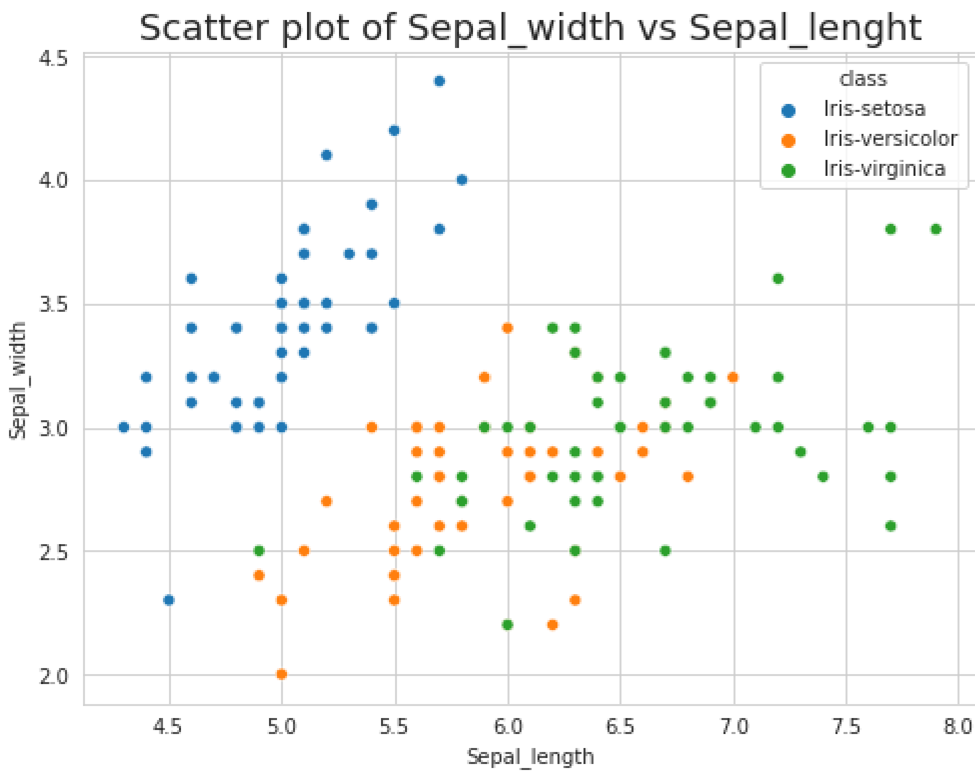
OBSERVATIONS

1. PETAL LENGHT AND PETAL WIDTH IS IMPORTANT FEATURE, IRIS SETOSA IS CLEARLY SEPARABLE FROM OTHER 2 CLASS BASED ON THESE 2 FEATURE
2.PETAL LENGHT AND PEATAL WIDTH FOLLOWS APPR. NORMAL DISTRIBUTION

2.4 SCATTERPLOT OF FEATURE SEPAL_LENGHT AND SEPAL_WIDTH

In [17]:
```
plt.figure(figsize=(8,6))
sns.set_style("whitegrid")
sns.scatterplot(x=data['Sepal_length'],
                y=data['Sepal_width'],
                hue=data['class'])
plt.title("Scatter plot of Sepal_width vs Sepal_lenght",fontsize=18)
```

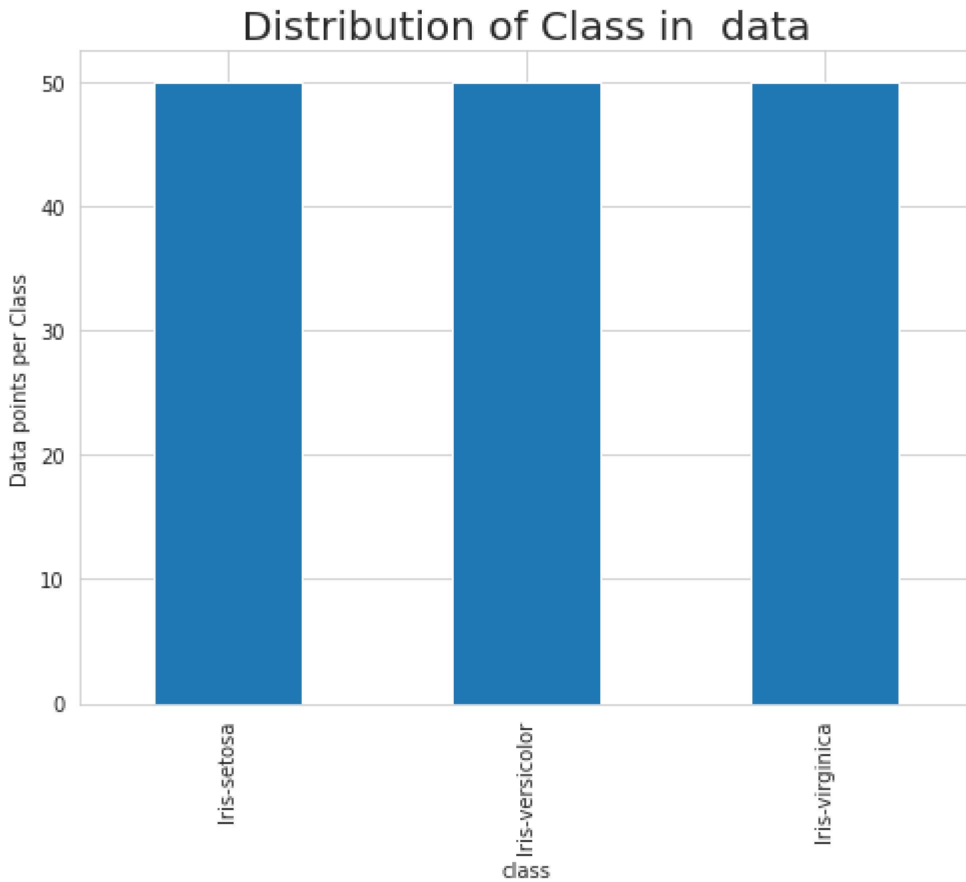
Out[17]:
```
Text(0.5, 1.0, 'Scatter plot of Sepal_width vs Sepal_lenght')
```



2.5 OUTPUT CLASS DISTRIBUTION

In [18]:
```
# it returns a dict, keys as class labels and values as the number of data poi
nts in that class
 ##https://pandas.pydata.org/pandas-docs/version/0.23.4/generated/pandas.DataF
rame.sortlevel.html
class_distribution = data['class'].value_counts().sort_index()

plt.figure()
plt.figure(figsize=(8,6))

my_colors = 'rgbkymc'
class_distribution.plot(kind='bar')
plt.xlabel('class')
plt.ylabel('Data points per Class')
plt.title('Distribution of Class in  data',fontsize=20)
plt.show()

# ref: argsort https://docs.scipy.org/doc/numpy/reference/generated/numpy.args
ort.html
# -(train_class_distribution.values): the minus sign will give us in decreasin
g order
sorted_yi = np.argsort(-class_distribution.values)
print('-'*80)
for i in sorted_yi:
    print('Number of data points in class', i+1, ':',
          class_distribution.values[i],
          '(', np.round((class_distribution.values[i]/data.shape[0]*100), 3),
'%)')
print('='*80)
```

```
<Figure size 432x288 with 0 Axes>
```




```
--------------------------------------------------------------------------------
---
Number of data points in class 1 : 50 ( 33.333 %)
Number of data points in class 2 : 50 ( 33.333 %)
Number of data points in class 3 : 50 ( 33.333 %)
================================================================================
===
```

3 TRAIN TEST SPILT 80-20

In [19]:
```
X = data.drop(['class'], axis=1)
y = data['class'].values
```

In [20]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X,
                                                    y,
                                                    stratify=y,
                                                    test_size=0.2)#80-20 split
```

3.1 SCALING THE FEATURES

In [21]:
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test) # TO AVOID DATALEAKAGE FIT_TRANSFORM
 IS USED ON ONLY TRAINDATA
```

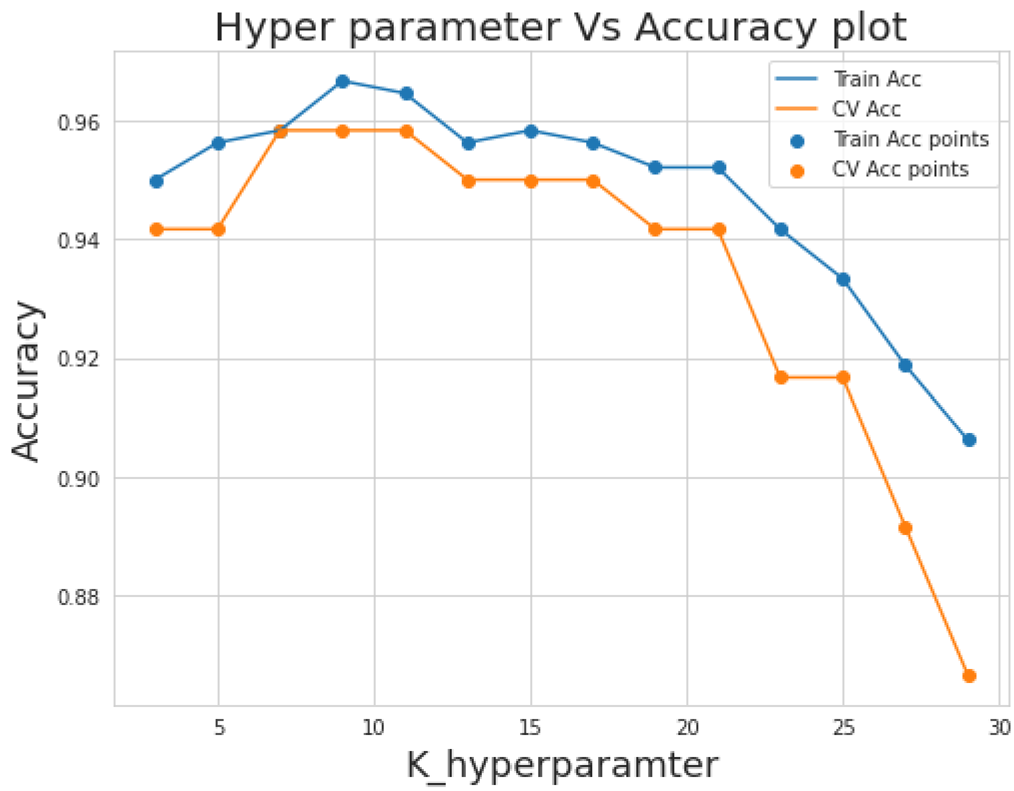
4 VARIOUS MODEL EXPERIMENTS

4.1 MODEL 1 KNN

4.1.1 KNN HYPERPARAMETER TUNE

In [23]:
```
#LR=LogisticRegression(random_state=0,penalty='l2',class_weight='balanced')
classifier_knn=KNeighborsClassifier()
parameters = {'n_neighbors':[3,5,7,9,11,13,15,17,19,21,23,25,27,29]}
clf = GridSearchCV(classifier_knn,parameters, cv= 5,
                   scoring='accuracy',return_train_score=True,
                   n_jobs=-1,verbose=2)

#https://stackoverflow.com/questions/56416576/getting-keyerror-from-sklearn-mo
del-selection-gridsearchcv

clf.fit(X_train_scaled, y_train)
results = pd.DataFrame.from_dict(clf.cv_results_)

#https://stackoverflow.com/questions/57136676/sklearn-model-selection-gridsear
chcv-is-throwing-keyerror-mean-train-score
train_acc= results['mean_train_score']
cv_acc = results['mean_test_score']
K_hyperparamter= results['param_n_neighbors']

plt.figure()
plt.figure(figsize=(8,6))
plt.plot(K_hyperparamter, train_acc, label='Train Acc')
# here: https://stackoverflow.com/a/48803361/4084039
plt.plot(K_hyperparamter, cv_acc, label='CV Acc')
#here: https://stackoverflow.com/a/48803361/4084039

plt.scatter(K_hyperparamter, train_acc, label='Train Acc points')
plt.scatter(K_hyperparamter, cv_acc, label='CV Acc points')

plt.legend()
plt.xlabel("K_hyperparamter",fontsize=18)
plt.ylabel("Accuracy",fontsize=18)
plt.title("Hyper parameter Vs Accuracy plot",fontsize=20)
plt.show()

best_K_hyperparamter=clf.best_params_
print("="*100)
print("best_K_hyperparamter:",best_K_hyperparamter)
best_K_hyperparamter=best_K_hyperparamter.get("n_neighbors")
print("="*100)
results.head()
```

```
Fitting 5 folds for each of 14 candidates, totalling 70 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done  70 out of  70 | elapsed:    0.5s finished

<Figure size 432x288 with 0 Axes>
```




```
================================================================================
========================
best_K_hyperparamter: {'n_neighbors': 7}
================================================================================
========================
```

Out[23]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_n_neighbors	parar
0	0.002466	0.000544	0.003093	0.000268	3	{'n_neighboı
1	0.001482	0.000577	0.003527	0.000853	5	{'n_neighboı
2	0.001148	0.000514	0.003613	0.001293	7	{'n_neighboı
3	0.000981	0.000057	0.002846	0.000095	9	{'n_neighboı
4	0.000904	0.000077	0.004863	0.003934	11	{'n_neighboı

4.1.2 BEST HYPERPARAMTER K=7 AND KNN MODEL

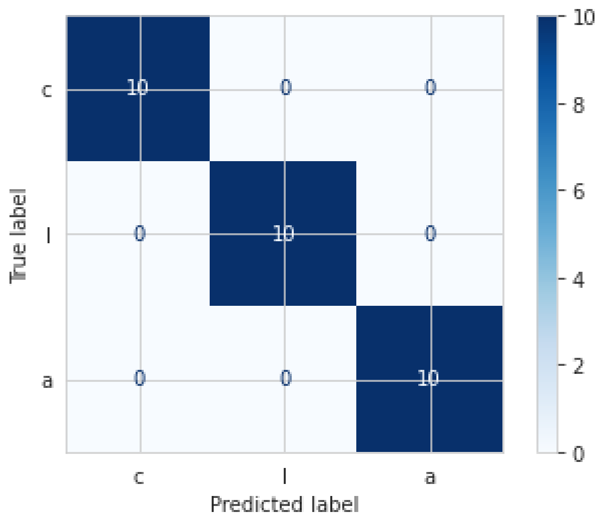
In [24]:
```
classifier_knn=KNeighborsClassifier(n_neighbors=7)
classifier_knn.fit(X_train_scaled, y_train)
```

Out[24]:
```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                     metric_params=None, n_jobs=None, n_neighbors=7, p=2,
                     weights='uniform')
```

4.1.3 RESULTS CONFUSION MATRIX AND CLASSIFICATION REPORT FOR KNN MODEL

In [29]:
```
y_pred = classifier_knn.predict(X_test_scaled)
confusion = confusion_matrix(y_test, y_pred)
print('Confusion Matrix_KNN\n')
print(confusion)

disp = plot_confusion_matrix(classifier_knn,
                             X_test_scaled,
                             y_test,
                             display_labels='class',
                             cmap=plt.cm.Blues)
plt.show()

print('\nClassification Report\n')
print(classification_report(y_test, y_pred,
                            target_names=['Iris-setosa', 'Iris-versicolor', 'I
ris-virginica']))
```

```
Confusion Matrix_KNN

[[10  0  0]
 [ 0 10  0]
 [ 0  0 10]]
```




```
Classification Report

                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00        10
Iris-versicolor       1.00      1.00      1.00        10
 Iris-virginica       1.00      1.00      1.00        10

       accuracy                           1.00        30
      macro avg       1.00      1.00      1.00        30
   weighted avg       1.00      1.00      1.00        30
```

In [30]:
```
predicted_class_label = classifier_knn.predict([[5.1,3.5,1.4,0.2]])
print('='*80)
print('''Classifier KNN Predicted class label for input "5.1,3.5,1.4,0.2"= '''
,
      predicted_class_label[0])
print('='*80)
```

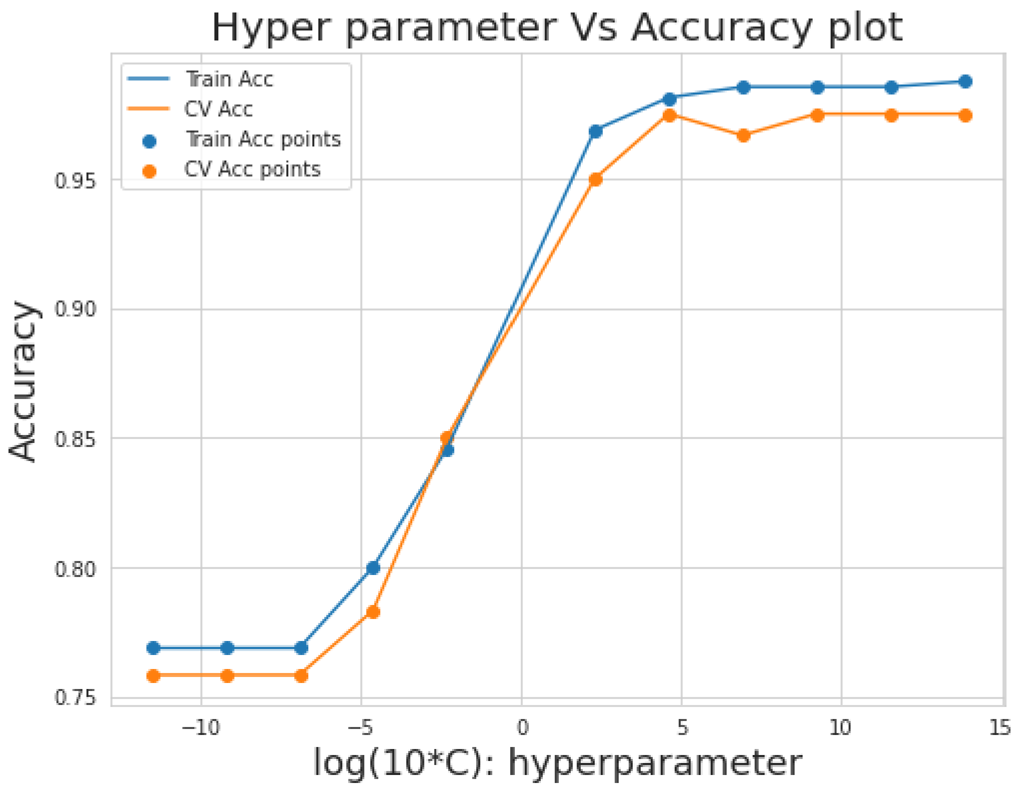
```
================================================================================
===
Classifier KNN Predicted class label for input "5.1,3.5,1.4,0.2"=  Iris-virgi
nica
================================================================================
===
```

4.2 MODEL 2LOGISTIC REGRESSION

4.2.1 HYPERPARAMETER TUNING FOR LOGISTIC REGRESSION

In [32]:
```
#LR=LogisticRegression(random_state=0,penalty='l2',class_weight='balanced')
LR=LogisticRegression(multi_class='multinomial', solver='lbfgs')
parameters = {'C':[0.000001,0.00001,0.0001,0.001,0.01,1,10,100,1000,10000,1000
00]}
clf = GridSearchCV(LR,parameters, cv= 5,
                   scoring='accuracy',return_train_score=True,
                   n_jobs=-1,verbose=2)

#https://stackoverflow.com/questions/56416576/getting-keyerror-from-sklearn-mo
del-selection-gridsearchcv

clf.fit(X_train_scaled, y_train)
results = pd.DataFrame.from_dict(clf.cv_results_)

#https://stackoverflow.com/questions/57136676/sklearn-model-selection-gridsear
chcv-is-throwing-keyerror-mean-train-score
train_acc= results['mean_train_score']
cv_acc = results['mean_test_score']
C_hyperparamter= results['param_C']

log_c_LR=[]
for i in C_hyperparamter:
    x=math.log(10*i)
    log_c_LR.append(x)


plt.figure()
plt.figure(figsize=(8,6))
plt.plot(log_c_LR, train_acc, label='Train Acc')
# here: https://stackoverflow.com/a/48803361/4084039
plt.plot(log_c_LR, cv_acc, label='CV Acc')
#here: https://stackoverflow.com/a/48803361/4084039

plt.scatter(log_c_LR, train_acc, label='Train Acc points')
plt.scatter(log_c_LR, cv_acc, label='CV Acc points')

plt.legend()
plt.xlabel("log(10*C): hyperparameter",fontsize=18)
plt.ylabel("Accuracy",fontsize=18)
plt.title("Hyper parameter Vs Accuracy plot",fontsize=20)

plt.show()

best_C=clf.best_params_
print("="*100)
print("Best_hyperparameter_best_C:",best_C)
Best_hyperparameter_best_C=best_C.get("C_hyperparamter")
print("="*100)
results.head(2)
```

```
Fitting 5 folds for each of 11 candidates, totalling 55 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done  55 out of  55 | elapsed:    0.6s finished

<Figure size 432x288 with 0 Axes>
```




```
================================================================================
========================
Best_hyperparameter_best_C: {'C': 10}
================================================================================
========================
```

Out[32]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_C	params	split0_test_s
0	0.007923	0.003737	0.000664	0.000115	1e-06	{'C': 1e-06}	0.79
1	0.006627	0.002908	0.000558	0.000083	1e-05	{'C': 1e-05}	0.79

4.2.2 BEST HYPERPARAMETER LOGISTIC REGRESSION

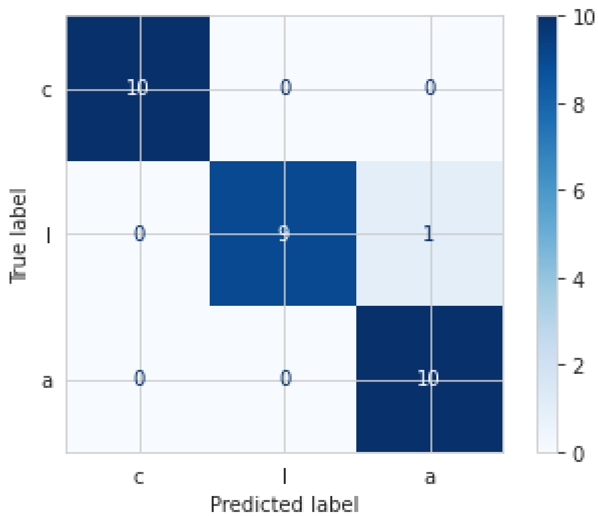
In [33]:
```
from sklearn.linear_model import LogisticRegression
classifier_LR = LogisticRegression(C=10,
                        multi_class='multinomial', solver='lbfgs')
classifier_LR.fit(X_train_scaled, y_train)
```

Out[33]:
```
LogisticRegression(C=10, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='multinomial', n_jobs=None, penalty='l2',
                   random_state=None, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
```

4.2.3 RESULTS AND CONFUSION MATRIX OF LOGISTIC REGRESSION

In [34]:
```
y_pred = classifier_LR.predict(X_test_scaled)
confusion = confusion_matrix(y_test, y_pred)
print('Confusion Matrix_LR\n')
print(confusion)

disp = plot_confusion_matrix(classifier_LR,
                             X_test_scaled,
                             y_test,
                             display_labels='class',
                             cmap=plt.cm.Blues)
plt.show()

print('\nClassification Report\n')
print(classification_report(y_test, y_pred,
                            target_names=['Iris-setosa', 'Iris-versicolor', 'I
ris-virginica']))
```

```
Confusion Matrix_LR

[[10  0  0]
 [ 0  9  1]
 [ 0  0 10]]
```




```
Classification Report

                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00        10
Iris-versicolor       1.00      0.90      0.95        10
 Iris-virginica       0.91      1.00      0.95        10

       accuracy                           0.97        30
      macro avg       0.97      0.97      0.97        30
   weighted avg       0.97      0.97      0.97        30
```

In [35]:
```
predicted_class_label = classifier_LR.predict([[5.1,3.5,1.4,0.2]])
print('='*80)
print('''Classifier LR Predicted class label for input "5.1,3.5,1.4,0.2"= ''',
      predicted_class_label[0])
print('='*80)
```

```
================================================================================
===
Classifier LR Predicted class label for input "5.1,3.5,1.4,0.2"=  Iris-versic
olor
================================================================================
===
```

4.3 MODEL 3 RANDOM FOREST

4.3.1 HYPERPARAMETER TUNING OF RANDOM FOREST MODEL

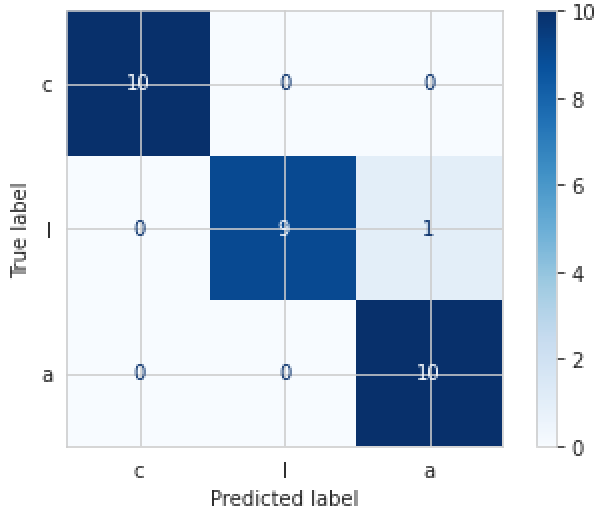
In [36]:
```
%timeit
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestClassifier
RF = RandomForestClassifier()
parameters = {'n_estimators': [10,15,20,25,30,35,40,45,50,55,60,65,70],
              'max_depth':[2, 3, 4, 5, 6, 7]}

clf = GridSearchCV(RF,parameters,cv= 5, scoring='accuracy',
                   return_train_score=True,n_jobs=-1,verbose=2)
clf.fit(X_train, y_train)
results = pd.DataFrame.from_dict(clf.cv_results_)

#https://stackoverflow.com/questions/57136676/sklearn-model-selection-gridsear
chcv-is-throwing-keyerror-mean-train-score
train_acc= results['mean_train_score']
cv_acc = results['mean_test_score']
n_estimators= results['param_n_estimators']
max_depth= results['param_max_depth']

best_n_estimators=clf.best_params_
print("="*100)
Best_hyperparameter_RF_n_estimators=best_n_estimators.get("n_estimators")
print("Best_hyperparameter_RF_n_estimators:",Best_hyperparameter_RF_n_estimato
rs)
print("="*100)
#results.head(2)

best_max_depth=clf.best_params_
print("="*100)
Best_hyperparameter_RF_max_depth=best_max_depth.get("max_depth")
print("Best_hyperparameter_RF_max_depth:",Best_hyperparameter_RF_max_depth)
print("="*100)
#results.head(2)
```

```
Fitting 5 folds for each of 78 candidates, totalling 390 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done  98 tasks      | elapsed:    5.3s

============================================================================
========================
Best_hyperparameter_RF_n_estimators: 20
============================================================================
========================
============================================================================
========================
Best_hyperparameter_RF_max_depth: 2
============================================================================
========================

[Parallel(n_jobs=-1)]: Done 390 out of 390 | elapsed:   22.2s finished
```

4.3.2 BEST HYPERPARAMETER RANDOM FOREST AND CLASSIFICATION REPORT AND CONFUSION MATRIX

In [37]:
```
classifier_RF = RandomForestClassifier(n_estimators = 20,
                                    max_depth=2,
                                    criterion = 'entropy',
                                    random_state = 42)
classifier_RF.fit(X_train, y_train)
y_pred = classifier_RF.predict(X_test)

confusion_matrix_RF = confusion_matrix(y_test, y_pred)
print('Confusion Matrix_RF\n')
print(confusion_matrix_RF)
disp = plot_confusion_matrix(classifier_RF,
                             X_test,
                             y_test,
                             display_labels='class',
                             cmap=plt.cm.Blues)
plt.show()


from sklearn.metrics import classification_report
print('\nClassification Report RF_Classifier\n')
print(classification_report(y_test, y_pred,
                            target_names=['Iris-setosa', 'Iris-versicolor', 'I
ris-virginica']))
```

```
Confusion Matrix_RF

[[10  0  0]
 [ 0  9  1]
 [ 0  0 10]]
```




```
Classification Report RF_Classifier

                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00        10
Iris-versicolor       1.00      0.90      0.95        10
 Iris-virginica       0.91      1.00      0.95        10

       accuracy                           0.97        30
      macro avg       0.97      0.97      0.97        30
   weighted avg       0.97      0.97      0.97        30
```

In [38]:

```
predicted_class_label = classifier_RF.predict([[5.1,3.5,1.4,0.2]])
print('='*80)
print('''classifier_RF Predicted class label for input  "5.1,3.5,1.4,0.2"= '''
,
      predicted_class_label[0])
print('='*80)
```

```
=============================================================================
===
classifier_RF Predicted class label for input  "5.1,3.5,1.4,0.2"=  Iris-setos
a
=============================================================================
===
```

4.4 MODEL 4 DECISION TREE

4.4.1 DECISION TREE MODEL TRAINING

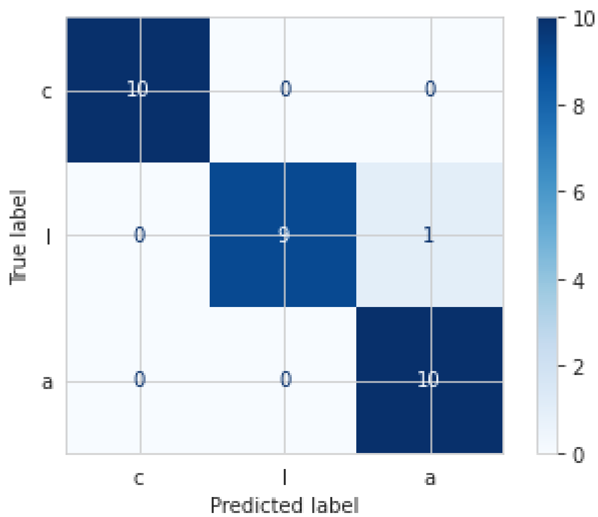
In [39]:
```
from sklearn.tree import DecisionTreeClassifier
classifier_DT=DecisionTreeClassifier(criterion= 'entropy')
classifier_DT.fit(X_train,y_train)
```

Out[39]:
```
DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, criterion='entropy',
                       max_depth=None, max_features=None, max_leaf_nodes=Non
e,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort='deprecated',
                       random_state=None, splitter='best')
```

4.4.2 RESULTS ,CONFUSION MATRIX AND CLASSIFICATION REPORT OF DECISION TREE

In [40]:
```
from sklearn.metrics import confusion_matrix
y_pred = classifier_DT.predict(X_test)
confusion = confusion_matrix(y_test, y_pred)
print('Confusion Matrix\n')
print(confusion)



disp = plot_confusion_matrix(classifier_DT,
                             X_test,
                             y_test,
                             display_labels='class',
                             cmap=plt.cm.Blues)
plt.show()


print('\nClassification Report\n')
print(classification_report(y_test, y_pred,
                            target_names=['Iris-setosa', 'Iris-versicolor', 'I
ris-virginica']))
```

```
Confusion Matrix

[[10  0  0]
 [ 0  9  1]
 [ 0  0 10]]
```




```
Classification Report

                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00        10
Iris-versicolor       1.00      0.90      0.95        10
 Iris-virginica       0.91      1.00      0.95        10

       accuracy                           0.97        30
      macro avg       0.97      0.97      0.97        30
   weighted avg       0.97      0.97      0.97        30
```

In [41]:
```
predicted_class_label = classifier_DT.predict([[5.1,3.5,1.4,0.2]])
print('='*80)
print('''Predicted class label for input "5.1,3.5,1.4,0.2"= ''',predicted_clas
s_label[0])
print('='*80)
```

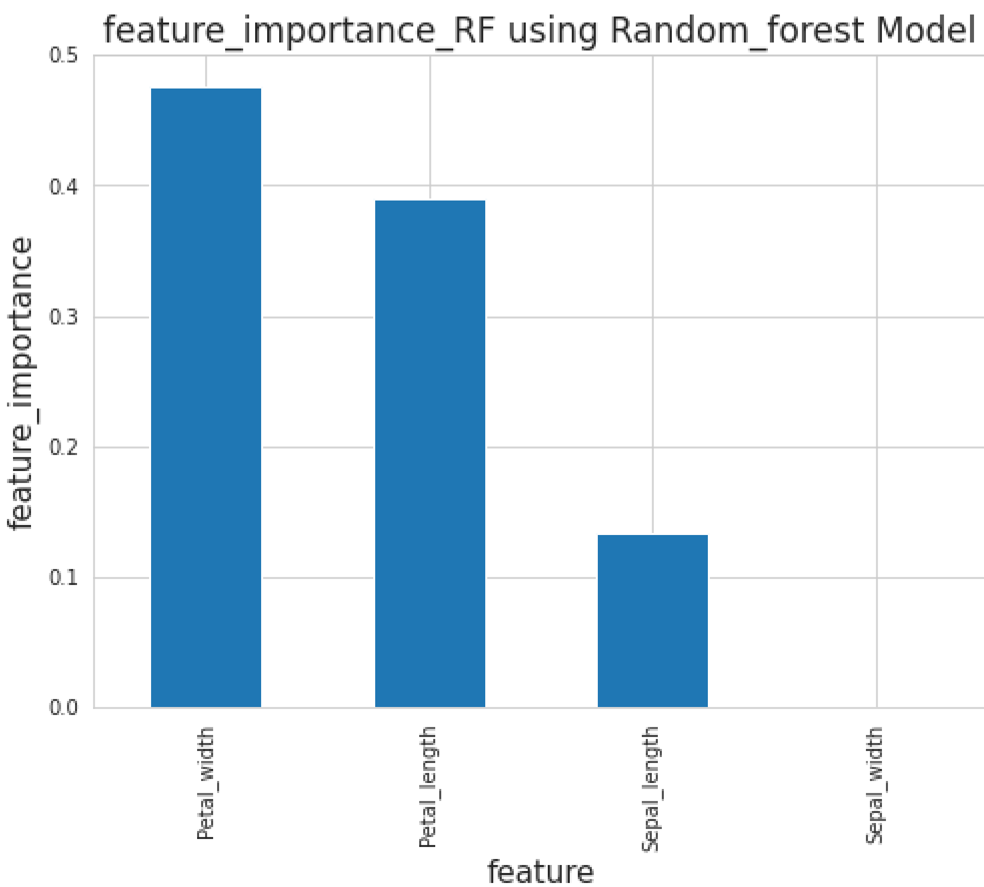
```
================================================================================
===
Predicted class label for input "5.1,3.5,1.4,0.2"=  Iris-setosa
================================================================================
===
```

5 FEATURE IMPORATNACE COMPARISON OF MODELS

5.1 FEATURE IMPORTANCE USING RANDOM FOREST MODEL

In [42]:
```
feature_importance_RF = pd.Series(classifier_RF.feature_importances_,
                                  index=['Sepal_length',
                                         'Sepal_width',
                                         'Petal_length',
                                         'Petal_width']).sort_values(ascending=False)

plt.figure()
ax=feature_importance_RF.plot.bar(figsize=(8,6))
ax.set_ylabel('feature_importance',fontsize=15)
ax.set_xlabel('feature',fontsize=15)
ax.set_title('feature_importance_RF using Random_forest Model',fontsize=17)
```

Out[42]:
```
Text(0.5, 1.0, 'feature_importance_RF using Random_forest Model')
```



5.2 FINAL PREDICTION FOR THE INPUT [5.1,3.5,1.4,0.2] USING DIFFERENT CLASSIFIERS

In [43]:
```
def final_prediction(model,name):
    '''
    This function takes model and model name as input
    predicts the output label for given Quesry point [5.1,3.5,1.4,0.2]
    '''

    predicted_class_label = model.predict([[5.1,3.5,1.4,0.2]])
    print('='*90)
    print(''' {} Predicted class label for input "5.1,3.5,1.4,0.2"= '''.format
(name),
          predicted_class_label[0])
    print('='*90)
```

In [46]:
```
list_model=[classifier_knn,classifier_LR,classifier_RF,classifier_DT]
model_name=['classifier_knn','classifier_LR','classifier_RF','classifier_DT']
for i in range(0,4):
    final_prediction(list_model[i],model_name[i])
```

```
==============================================================================
============
 classifier_knn Predicted class label for input "5.1,3.5,1.4,0.2"=  Iris-virg
inica
==============================================================================
============
==============================================================================
============
 classifier_LR Predicted class label for input "5.1,3.5,1.4,0.2"=  Iris-versi
color
==============================================================================
============
==============================================================================
============
 classifier_RF Predicted class label for input "5.1,3.5,1.4,0.2"=  Iris-setos
a
==============================================================================
============
==============================================================================
============
 classifier_DT Predicted class label for input "5.1,3.5,1.4,0.2"=  Iris-setos
a
==============================================================================
============
```

In [15]:
```
from prettytable import PrettyTable

x = PrettyTable()

x.field_names = ["SR.NO.","Model", "ACCURACY",
                 "EXPECTED_RESULT_ON_SAMPLE_INPUT_“5.1,3.5,1.4,0.2”"]

x.add_row(["1","KNN", '1','Iris-versicolor'])
x.add_row(["2","LOGISTIC_REGRESSION", '0.97','Iris-versicolor'])
x.add_row(["3","RANDOM_FOREST", '0.97','Iris-setosa'])
x.add_row(["4","DECISION_TREE", '0.97','Iris-setosa'])

print(x)
```

```
+--------+---------------------+----------+---------------------------------
-----------------+
| SR.NO. |         Model       | ACCURACY | EXPECTED_RESULT_ON_SAMPLE_INPUT
_“5.1,3.5,1.4,0.2” |
+--------+---------------------+----------+---------------------------------
-----------------+
|   1    |          KNN        |    1     |                  Iris-versicolor
|
|   2    | LOGISTIC_REGRESSION |   0.97   |                  Iris-versicolor
|
|   3    |    RANDOM_FOREST    |   0.97   |                    Iris-setosa
|
|   4    |    DECISION_TREE    |   0.97   |                    Iris-setosa
|
+--------+---------------------+----------+---------------------------------
-----------------+
```

OBSERVATION:

1.THOUGH KNN IS PERFORMING WELL IN TERMS OF ACCURACY IT IS GIVING WRONG PREDICTION FOR UNKNOWN QUERY POINT

2.TREE BASED ALGORITHM IS PERFORMING WELL ON UNKNOWN QUERY POINT

3.AS THERE ARE LESS FEATURES TREE BASED ALGORTHM WILL BE PERFROMING GOOD

4.*THERFORE FINAL MODEL IS RANDOM FOREST*