In [109	#Bishop's Universirty #Statistical Learning (Winter2022) - Dr Dorra Riahi # Members # Razieh Shahsavar(002341606) - Maryam Bayatzadeh(002338161) # Bahareh Hadadnosrati(002312944) - Yasaman Mardan(002341666)
In [104	<pre># Importing the libraries import numpy as np import matplotlib.pyplot as plt import pandas as pd</pre>
In [85]:	<pre># Importing the dataset dataset = pd.read_csv('D:\\Razieh\\statisticalLearning2022\\submit\\iris.csv')</pre>
	ld SepalLengthCm SepalWidthCm PetalLengthCm PetalWidthCm Species 1 1 5.1 3.5 1.4 0.2 Iris-setosa
	1 2 4.9 3.0 1.4 0.2 Iris-setosa 2 3 4.7 3.2 1.3 0.2 Iris-setosa 3 4 4.6 3.1 1.5 0.2 Iris-setosa 4 5 5.0 3.6 1.4 0.2 Iris-setosa
In [86]:	<pre># Splitting the dataset into the Training set and Test set X = dataset.iloc[:, 1:-1].values</pre>
	<pre>y = dataset.iloc[:,-1].values from sklearn.model_selection import train_test_split X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.40, random_state = 0) print(X.shape) #150rows and 4 columns print(y.shape) print(f"x_Training={X_train}")</pre>
	<pre>print(f"y_Training={y_train}") #conver picies column(y_pred) to numerical by onehotencoding</pre>
	<pre>from sklearn.preprocessing import LabelEncoder, OneHotEncoder onehotencoder = OneHotEncoder(categories='auto') y_test_encoder= onehotencoder.fit_transform(y_test.reshape(-1,1)) # y - will be sparse matrix of type '<class 'numpy.float64'=""> # if you want it to be a array you need to print(f"y_Test(OneHotEncoding)={y_test_encoder.toarray()}")</class></pre>
	<pre># Plot the relation of each feature with each species(simple diagram without any models) plt.xlabel('Features') plt.ylabel('Species') pltX = dataset.loc[:, 'SepalLengthCm']</pre>
	<pre>pltY = dataset.loc[:,'Species'] plt.scatter(pltX, pltY, color='blue', label='sepal_length') pltX = dataset.loc[:, 'SepalWidthCm'] pltY = dataset.loc[:,'Species']</pre>
	<pre>plt.scatter(pltX, pltY, color='green', label='sepal_width') pltX = dataset.loc[:, 'PetalLengthCm'] pltY = dataset.loc[:,'Species'] plt.scatter(pltX, pltY, color='red', label='petal_length')</pre>
	<pre>pltX = dataset.loc[:, 'PetalWidthCm'] pltY = dataset.loc[:, 'Species'] plt.scatter(pltX, pltY, color='black', label='petal_width') plt.title("Simple Iris(without any Model)") plt.legend(loc=4, prop={'size':8})</pre>
	plt.show() (150, 4) (150,) x_Training=[[6. 3.4 4.5 1.6]
	[4.8 3.1 1.6 0.2] [5.8 2.7 5.1 1.9] [5.6 2.7 4.2 1.3] [5.6 2.9 3.6 1.3] [5.5 2.5 4. 1.3] [6.1 3. 4.6 1.4]
	[7.2 3.2 6. 1.8] [5.3 3.7 1.5 0.2] [4.3 3. 1.1 0.1] [6.4 2.7 5.3 1.9] [5.7 3. 4.2 1.2] [5.4 3.4 1.7 0.2]
	[5.7 4.4 1.5 0.4] [6.9 3.1 4.9 1.5] [4.6 3.1 1.5 0.2] [5.9 3. 5.1 1.8] [5.1 2.5 3. 1.1]
	[4.6 3.4 1.4 0.3] [6.2 2.2 4.5 1.5] [7.2 3.6 6.1 2.5] [5.7 2.9 4.2 1.3] [4.8 3. 1.4 0.1] [7.1 3. 5.9 2.1]
	[6.9 3.2 5.7 2.3] [6.5 3. 5.8 2.2] [6.4 2.8 5.6 2.1] [5.1 3.8 1.6 0.2] [4.8 3.4 1.6 0.2] [6.5 3.2 5.1 2.]
	[6.7 3.3 5.7 2.1] [4.5 2.3 1.3 0.3] [6.2 3.4 5.4 2.3] [4.9 3. 1.4 0.2] [5.7 2.5 5. 2.] [6.9 3.1 5.4 2.1]
	[4.4 3.2 1.3 0.2] [5. 3.6 1.4 0.2] [7.2 3. 5.8 1.6] [5.1 3.5 1.4 0.3] [4.4 3. 1.3 0.2]
	[5.4 3.9 1.7 0.4] [5.5 2.3 4. 1.3] [6.8 3.2 5.9 2.3] [7.6 3. 6.6 2.1] [5.1 3.5 1.4 0.2] [4.9 3.1 1.5 0.1]
	[5.2 3.4 1.4 0.2] [5.7 2.8 4.5 1.3] [6.6 3. 4.4 1.4] [5. 3.2 1.2 0.2] [5.1 3.3 1.7 0.5] [6.4 2.9 4.3 1.3]
	[5.4 3.4 1.5 0.4] [7.7 2.6 6.9 2.3] [4.9 2.4 3.3 1.] [7.9 3.8 6.4 2.] [6.7 3.1 4.4 1.4]
	[5.2 4.1 1.5 0.1] [6. 3. 4.8 1.8] [5.8 4. 1.2 0.2] [7.7 2.8 6.7 2.] [5.1 3.8 1.5 0.3] [4.7 3.2 1.6 0.2]
	[7.4 2.8 6.1 1.9] [5. 3.3 1.4 0.2] [6.3 3.4 5.6 2.4] [5.7 2.8 4.1 1.3] [5.8 2.7 3.9 1.2] [5.7 2.6 3.5 1.]
	[5.7 2.6 3.5 1.] [6.4 3.2 5.3 2.3] [6.7 3. 5.2 2.3] [6.3 2.5 4.9 1.5] [6.7 3. 5. 1.7] [5. 3. 1.6 0.2] [5.5 2.4 3.7 1.]
	[6.7 3.1 5.6 2.4] [5.8 2.7 5.1 1.9] [5.1 3.4 1.5 0.2] [6.6 2.9 4.6 1.3] [5.6 3. 4.1 1.3]
	[5.9 3.2 4.8 1.8] [6.3 2.3 4.4 1.3] [5.5 3.5 1.3 0.2] [5.1 3.7 1.5 0.4] [4.9 3.1 1.5 0.1] [6.3 2.9 5.6 1.8] [5.8 2.7 4.1 1.1]
	[5.8 2.7 4.1 1.] [7.7 3.8 6.7 2.2] [4.6 3.2 1.4 0.2]] y_Training=['Iris-versicolor' 'Iris-setosa' 'Iris-virginica' 'Iris-versicolor' 'Iri
	'Iris-setosa' 'Iris-setosa' 'Iris-versicolor' 'Iris-setosa' 'Iris-virginica' 'Iris-versicolor' 'Iris-setosa' 'Iris-versicolor' 'Iris-virginica' 'Iris-versicolor' 'Iris-setosa' 'Iris-virginica' 'Iris-virginica' 'Iris-virginica' 'Iris-virginica' 'Iris-virginica' 'Iris-virginica' 'Iris-virginica' 'Iris-setosa' 'Iris-setosa' 'Iris-virginica' 'Iris-virginica' 'Iris-setosa' 'Iris-virginica' 'Iris-setosa' 'Iris-virginica' 'Iris-virginica' 'Iris-virginica' 'Iris-setosa'
	'Iris-setosa' 'Iris-setosa' 'Iris-virginica' 'Iris-setosa' 'Iris-setosa' 'Iris-setosa' 'Iris-versicolor' 'Iris-virginica' 'Iris-virginica' 'Iris-setosa' 'Iris-setosa' 'Iris-setosa' 'Iris-versicolor' 'Iris-versicolor' 'Iris-setosa' 'Iris-setosa' 'Iris-versicolor' 'Iris-setosa' 'Iris-virginica' 'Iris-versicolor'
	'Iris-versicolor' 'Iris-setosa' 'Iris-virginica' 'Iris-setosa' 'Iris-virginica' 'Iris-setosa' 'Iris-setosa' 'Iris-virginica' 'Iris-setosa' 'Iris-virginica' 'Iris-versicolor' 'Iris-versicolor' 'Iris-versicolor' 'Iris-virginica' 'Iris-virginica' 'Iris-versicolor' 'Iris-versicolor' 'Iris-setosa' 'Iris-versicolor'
	'Iris-versicolor' 'Iris-versicolor' 'Iris-setosa' 'Iris-setosa' 'Iris-setosa' 'Iris-versicolor' 'Iris-
	[0. 0. 1.] [1. 0. 0.] [0. 0. 1.] [1. 0. 0.] [0. 1. 0.] [0. 1. 0.]
	[0. 1. 0.] [0. 0. 1.] [0. 1. 0.] [0. 1. 0.] [0. 1. 0.]
	[0. 1. 0.] [1. 0. 0.] [0. 1. 0.] [0. 1. 0.] [1. 0. 0.] [1. 0. 0.]
	[0. 0. 1.] [0. 1. 0.] [1. 0. 0.] [1. 0. 0.] [0. 0. 1.] [1. 0. 0.]
	[1. 0. 0.] [0. 1. 0.] [1. 0. 0.] [1. 0. 0.] [1. 0. 0.] [1. 0. 1.]
	[0. 1. 0.] [1. 0. 0.] [0. 0. 1.] [0. 0. 1.] [0. 1. 0.] [1. 0. 0.]
	[0. 1. 0.] [0. 1. 0.] [0. 1. 0.] [0. 0. 1.] [1. 0. 0.] [0. 0. 1.]
	[1. 0. 0.] [1. 0. 0.] [0. 1. 0.] [0. 0. 1.] [0. 0. 1.]
	[0. 0. 1.] [0. 0. 1.] [0. 1. 0.] [0. 1. 0.] [0. 1. 0.]
	[0. 0. 1.] [0. 0. 1.] [0. 0. 1.] [0. 0. 1.] [0. 1. 0.] [0. 1. 0.]
	Simple Iris(without any Model) Iris-virginica
	Iris-versicolor -
	Iris-setosa 0 1 2 3 4 5 6 7 8 Features
In [87]:	<pre>#preprocessing befor Model from sklearn.preprocessing import StandardScaler sc = StandardScaler() X_train = sc.fit_transform(X_train) X_test = sc.transform(X_test)</pre>
In [88]:	# Fitting Logistic Regression to the Training set - and calculate time consuming import time from sklearn.linear_model import LogisticRegression
	<pre>classifier = LogisticRegression(random_state = 0) start=time.time() classifier.fit(X_train, y_train) #training the model stop=time.time() Logistic_Time=round(stop - start,7) print(f"Logistic Regression[Training time]={Logistic_Time}s")</pre>
In [89]:	Logistic Regression[Training time]=0.0070024s #TEst the model y_pred=classifier.predict(X_test)
	<pre># print(f"y_prediction={y_pred}") from sklearn.metrics import accuracy_score accuracy=accuracy_score(y_test,y_pred)</pre>
	<pre>#show accuracy of prediction print(f"Logistic Regression[Prediction accuracy]={round(accuracy,2)}") #convert picies column(y_pred) to numerical by oneHotencoding from sklearn.preprocessing import LabelEncoder, OneHotEncoder</pre>
	<pre>onehotencoder = OneHotEncoder(categories='auto') y_pred_encoder= onehotencoder.fit_transform(y_pred.reshape(-1,1)) # #y - will be sparse matrix of type '<class 'numpy.float64'=""> # #if you want it to be a array you need to # print(f"y_prediction(OneHtEncoder)={y_pred_encoder.toarray()}")</class></pre>
	<pre>#calculate Training Error rate(MSE) # print(y_pred_encoder.shape) # print(y_test_encoder.shape) # print(f"subtract={ (y_test_encoder-y_pred_encoder).shape}") mse_Logistic=mean_squared_error(y_test_encoder.toarray(),y_pred_encoder.toarray()) print(f"Logistic Regression(Training Error Rate)={mse_Logistic}")</pre>
	Logistic Regression[Prediction accuracy]=0.93 Logistic Regression(Training Error Rate)=0.044444444444444444444444444444444444
	<pre>from sklearn.neighbors import KNeighborsClassifier classifier1=KNeighborsClassifier (n_neighbors=5, metric='minkowski', p=2) start=time.time() classifier1.fit(X_train, y_train) stop=time.time() K_NN_Time=round(stop - start,7)</pre>
In [91]:	<pre>print(f"K_NN[Training time]={K_NN_Time}s") K_NN[Training time]=0.0009785s #TEst the K_NN model and show accuracy of prediction</pre>
	<pre>y_pred=classifier1.predict(X_test) # print(y_pred) #show accuracy of prediction from sklearn.metrics import accuracy_score accuracy1=accuracy_score(y_test,y_pred)</pre>
	<pre>print(f"K_NN[Prediction accuracy]={round(accuracy1,2)}") #convert picies column(y_pred) to numerical by onehotencoding from sklearn.preprocessing import LabelEncoder, OneHotEncoder onehotencoder = OneHotEncoder(categories='auto')</pre>
	<pre>onehotencoder = OneHotEncoder(categories='auto') y_pred_encoder= onehotencoder.fit_transform(y_pred.reshape(-1,1)) #calculate Training Error rate(MSE) mse_K_NN=mean_squared_error(y_test_encoder.toarray(),y_pred_encoder.toarray()) print(f"K_NN(Training Error Rate)={mse_K_NN}")</pre>
	<pre>K_NN[Prediction accuracy]=0.93 K_NN(Training Error Rate)=0.044444444444444444444444444444444444</pre>
	<pre>classifier2=SVC(kernel='linear',random_state=0) start=time.time() classifier2.fit(X_train,y_train) stop=time.time() SVM_Time=round(stop - start,7) print(f"SVM[Training time]={SVM_Time}s")</pre>
In [93]:	SVM[Training time]=0.0029862s #TEst the SVM model and show accuracy of prediction y_pred2=classifier2.predict(X_test)
	<pre>y_pred2=classifier2.predict(X_test) # print(y_pred) #show accuracy of prediction from sklearn.metrics import accuracy_score accuracy2=accuracy_score(y_test,y_pred2) print(f"SVM[Prediction accuracy]={round(accuracy2,2)}")</pre>
	<pre>print(f"SVM[Prediction accuracy]={round(accuracy2,2)}") #convert picies column(y_pred) to numerical by onehotencoding from sklearn.preprocessing import LabelEncoder, OneHotEncoder onehotencoder = OneHotEncoder(categories='auto')</pre>
	<pre>y_pred_encoder2= onehotencoder.fit_transform(y_pred2.reshape(-1,1)) #calculate Training Error rate(MSE) mse_SVM=mean_squared_error(y_test_encoder.toarray(),y_pred_encoder2.toarray()) print(f"SVM(Training Error Rate)={mse_SVM}")</pre>
	SVM[Prediction accuracy]=0.93 SVM(Training Error Rate)=0.044444444444444444444444444444444444
	<pre>#plot Training error rate y_axis=[mse_Logistic,mse_K_NN,mse_SVM] x_axis=["Logistic Regression","K_NN","SVM"] New_Colors = ['green', 'blue', 'purple'] plt.bar(x_axis,y_axis,color=New_Colors) plt.title('Training Error Rate')</pre>
	<pre>plt.ylabel('MSE') plt.xlabel('Classification Models') plt.grid(True) plt.show() #plot accuracy of Prediction</pre>
	<pre>y_axis=[accuracy,accuracy2] x_axis=["Logistic Regression","K_NN","SVM"] New_Colors = ['red','gray','orange'] plt.bar(x_axis,y_axis,color=New_Colors) plt.title('Result Robustness')</pre>
	<pre>plt.ylabel('Result Robustness(accuracy)') plt.xlabel('Classification Models') plt.grid(True) plt.show()</pre>
	<pre>#plot Time Consuming y_axis=[Logistic_Time, K_NN_Time, SVM_Time] x_axis=["Logistic Regression", "K_NN", "SVM"] New_Colors = ['brown', 'cyan', 'yellow'] plt.bar(x_axis,y_axis,color=New_Colors) plt.title(' Time Consuming') nlt.ylabel(' Time Consuming')</pre>
	plt.ylabel(' Time Consuming') plt.xlabel('Classification Models') plt.grid(True) plt.show() Training Error Rate
	Training Error Rate 0.04 0.03
	Logistic Regression K_NN SVM Classification Models
	Result Robustness Result Robustness
	0.4 Out of the series of the s
	0.0 Logistic Regression K_NN SVM Classification Models
	0.007 0.006
	0.004 - 0.003
	0.002 0.001 Logistic Regression K_NN SVM Classification Models
In []:	