

## Experiment-1

**Aim:** Implement the Naive Bayes learning algorithm on Balance Scale Dataset.

### **Code:**

```
Mdl = fitcnb(BCDE,A)
[label,Posterior,Cost] = predict(Mdl,row)
[xx1, xx2] = meshgrid(4:.01:8,2:.01:4.5);
XGrid = [xx1(:) xx2(:)];
figure('Units','Normalized','Position',[0.25,0.55,0.4,0.35]);
sz = size(xx1);
```

## Output:

Mdl =

ClassificationNaiveBayes

PredictorNames: {'VarName2' 'VarName3' 'VarName4' 'VarName5'}

ResponseName: 'B'

CategoricalPredictors: []

ClassNames: [B L R]

ScoreTransform: 'none'

NumObservations: 625

DistributionNames: {'normal' 'normal' 'normal' 'normal'}

DistributionParameters: {3×4 cell}

Properties, Methods

label =

2×1 categorical array

L  
R

Posterior =

0.2723	0.3638	0.3638
0.2108	0.2291	0.5601

Cost =

0.7277	0.6362	0.6362
0.7892	0.7709	0.4399

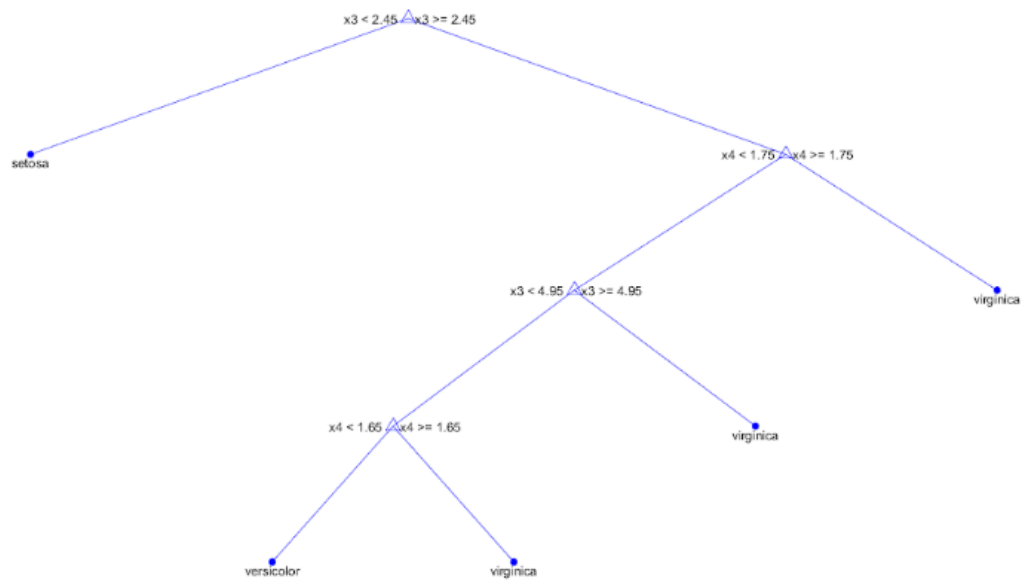
## Experiment-2

**Aim:** Classify the iris dataset using Decision Tree learning algorithm.  
Calculate the classification accuracy using 5-fold cross validation.

**Code:**

```
load fisheriris
Mdl = fitctree(meas,species);
CVMdl = crossval(Mdl,'Kfold',5);
L = kfoldLoss(CVMdl);
%view(Mdl)
view(Mdl,'Mode','graph');
```

**Output:**



```

Command Window

>> decision_tree
>> Mdl

Mdl =

    ClassificationTree
        ResponseName: 'Y'
        CategoricalPredictors: []
        ClassNames: {'setosa' 'versicolor' 'virginica'}
        ScoreTransform: 'none'
        NumObservations: 150

    Properties, Methods

>> CVMdl

CVMdl =

    classreg.learning.partition.ClassificationPartitionedModel
        CrossValidatedModel: 'Tree'
        PredictorNames: {'x1' 'x2' 'x3' 'x4'}
        ResponseName: 'Y'
        NumObservations: 150
        KFold: 5
        Partition: [1x1 cvpartition]
        ClassNames: {'setosa' 'versicolor' 'virginica'}
        ScoreTransform: 'none'

    Properties, Methods

>> L

L =

    0.0533
  
```

## Experiment-3

**Aim:** Implement the K-means algorithm and apply it on any two datasets. Evaluate performance by measuring the Euclidean distance of each example from its class center. Test the performance of algorithm as a function of k.

### **Code:**

#### **1) Fisheriris Dataset**

```
load fisheriris
X = meas(:,3:4);
figure;
plot(X(:,1),X(:,2),'k*','MarkerSize',5);
title 'Fisher''s Iris Data';
xlabel 'Petal Lengths (cm)';
ylabel 'Petal Widths (cm)';
rng(1); % For reproducibility
eva = evalclusters(meas,'kmeans','CalinskiHarabasz','KList',
[1:4]);
[idx,C,sumD,D] = kmeans(X,3);
x1 = min(X(:,1)):0.01:max(X(:,1));
x2 = min(X(:,2)):0.01:max(X(:,2));
[x1G,x2G] = meshgrid(x1,x2);
XGrid = [x1G(:),x2G(:)]; % Defines a fine grid on the plot
idx2Region = kmeans(XGrid,3,'MaxIter',1,'Start',C);
figure;
gscatter(XGrid(:,1),XGrid(:,2),idx2Region,...
[0,0.75,0.75;0.75,0,0.75;0.75,0.75,0], '..');
hold on;
plot(X(:,1),X(:,2),'k*','MarkerSize',5);
title 'Fisher''s Iris Data';
xlabel 'Petal Lengths (cm)';
ylabel 'Petal Widths (cm)';
legend('Region 1','Region 2','Region
3','Data','Location','SouthEast');
hold off;
```

## Output:

Command Window			Command Window		
>> D					
D =					
0.005960000000000	20.981423611111104	9.537352071005916	0.028360000000000	21.830590277777770	10.121198224852071
0.005960000000000	20.981423611111104	9.537352071005916	0.003560000000000	20.152256944444435	8.973505917159763
0.028360000000000	21.830590277777770	10.121198224852071	0.029160000000000	21.473090277777771	9.902736686390533
0.003560000000000	20.152256944444435	8.973505917159763	0.029160000000000	21.473090277777771	9.902736686390533
0.005960000000000	20.981423611111104	9.537352071005916	0.028360000000000	21.830590277777770	10.121198224852071
0.080360000000000	17.858923611111102	7.488890532544377	0.144360000000000	18.033090277777767	7.675813609467454
0.006760000000000	20.623923611111103	9.318890532544378	0.215560000000000	20.981423611111104	9.537352071005916
0.003560000000000	20.152256944444435	8.973505917159763	0.006760000000000	20.623923611111103	9.318890532544378
0.005960000000000	20.981423611111104	9.537352071005916	0.021160000000000	19.343090277777769	8.429659763313609
0.022760000000000	20.529756944444436	9.211967455621300	0.005960000000000	20.981423611111104	9.537352071005916
0.003560000000000	20.152256944444435	8.973505917159763	0.003560000000000	20.152256944444435	8.973505917159763
0.021160000000000	19.343090277777769	8.429659763313609	0.005960000000000	20.981423611111104	9.537352071005916
0.025160000000000	21.358923611111102	9.775813609467454	11.816360000000000	1.208923611111109	0.188890532544379
0.152360000000000	23.966423611111097	11.587352071005915	10.801959999999999	1.489756944444442	0.078121301775148
0.070760000000000	22.699756944444434	10.725044378698223	13.392360000000002	0.773090277777776	0.422736686390533
0.025160000000000	19.457256944444435	8.556582840236684	7.552359999999998	3.090590277777774	0.074275147928994
0.049960000000000	21.135590277777769	9.704275147928994	11.419559999999997	1.280590277777776	0.134275147928994
0.006760000000000	20.623923611111103	9.318890532544378	10.340359999999999	1.744756944444442	0.055044378698225
0.059560000000000	18.196423611111101	7.687352071005915	12.317959999999999	0.993923611111109	0.251967455621302
0.004360000000000	19.794756944444437	8.755044378698223	3.946759999999999	6.347256944444441	1.056582840236686
0.058760000000000	18.553923611111102	7.905813609467454	10.957959999999996	1.535590277777776	0.111198224852071
0.025160000000000	19.457256944444435	8.556582840236684	7.275559999999999	3.282256944444441	0.139659763313610
0.215560000000000	24.498090277777766	11.992736686390531	4.721959999999999	5.468923611111107	0.708890532544378
0.121160000000000	17.541423611111099	7.310428994082838	9.069160000000000	2.237256944444441	0.029659763313610
0.193960000000000	17.035590277777771	6.918121301775147	7.009959999999999	3.623090277777774	0.189659763313609
0.021160000000000	19.343090277777769	8.429659763313609	11.816360000000000	1.208923611111109	0.188890532544379
0.042760000000000	18.648090277777769	8.012736686390531	5.681960000000000	4.527256944444440	0.449659763313609
0.003560000000000	20.152256944444435	8.973505917159763	9.963560000000001	1.836423611111107	0.020428994082840
0.005960000000000	20.981423611111104	9.537352071005916	10.801959999999999	1.489756944444442	0.078121301775148
0.021160000000000	19.343090277777769	8.429659763313609	7.527559999999997	3.313923611111108	0.145813609467456
0.021160000000000	19.343090277777769	8.429659763313609	10.801959999999999	1.489756944444442	0.078121301775148
0.025160000000000	19.457256944444435	8.556582840236684	6.673159999999999	3.754756944444440	0.195044378698225
0.022760000000000	20.529756944444436	9.211967455621300	13.557159999999998	0.689756944444443	0.491198224852071
0.005960000000000	20.981423611111104	9.537352071005916	7.552359999999998	3.090590277777774	0.074275147928994
0.003560000000000	20.152256944444435	8.973505917159763	13.392360000000002	0.773090277777776	0.422736686390533
0.070760000000000	22.699756944444434	10.725044378698223	11.394760000000000	1.503923611111108	0.205813609467456
			9.165159999999997	2.223090277777775	0.002736686390533
			9.963560000000001	1.836423611111107	0.020428994082840
			12.473959999999998	1.039756944444443	0.285044378698225
			14.631559999999999	0.468923611111110	0.661967455621302

>> eva

eva =

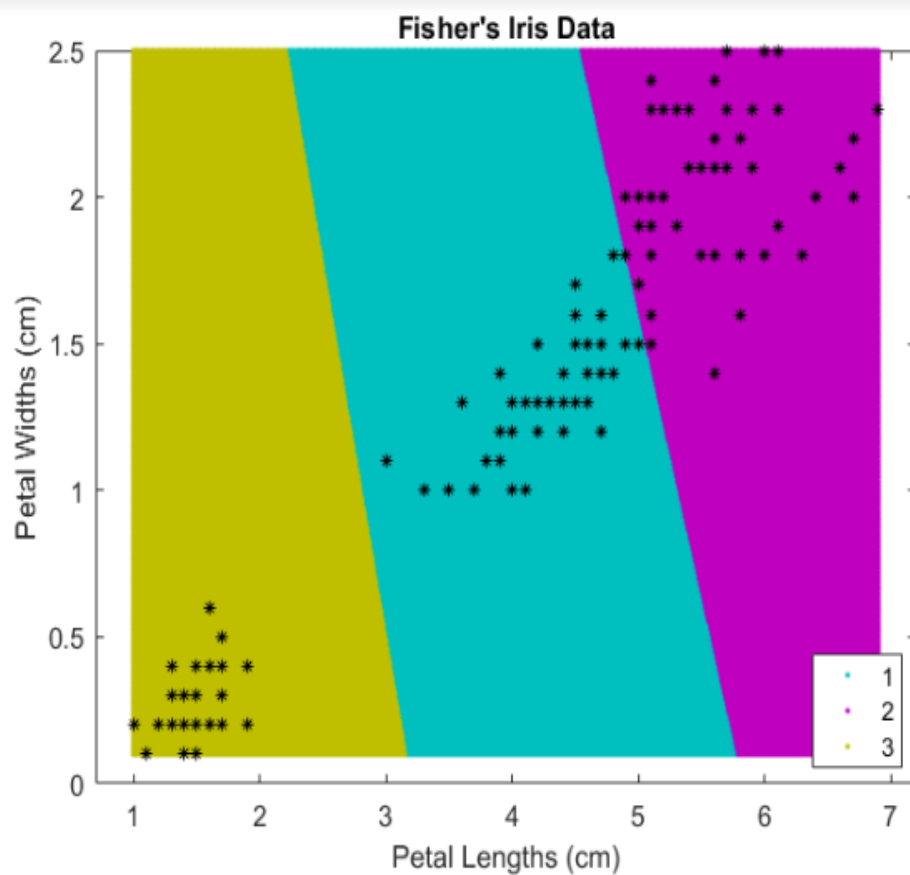
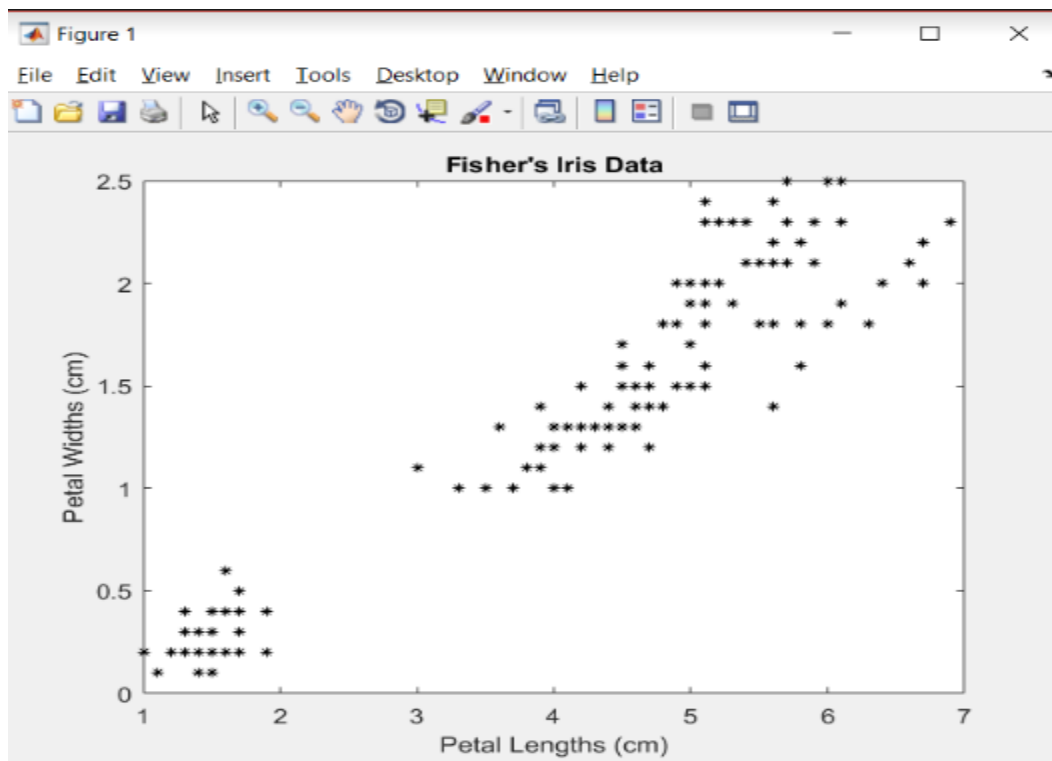
[CalinskiHarabaszEvaluation](#) with properties:

NumObservations: 150

InspectedK: [1 2 3 4]

CriterionValues: [NaN 5.139245459802769e+02 5.616277566296201e+02 5.304871420421677e+02]

OptimalK: 3



## Code:

### 1) Kmeans Dataset

```
load kmeansdata
Y = X(:,3:4);
figure;
plot(Y(:,1),Y(:,2),'k*','MarkerSize',5);
title 'K-Means Data';
xlabel 'X';
ylabel 'Y';
rng(1); % For reproducibility
eva = evalclusters(X,'kmeans','CalinskiHarabasz','KList',[1:4]);
[idx,C,sumD,D] = kmeans(Y,4);
x1 = min(Y(:,1)):0.01:max(Y(:,1));
x2 = min(Y(:,2)):0.01:max(Y(:,2));
[x1G,x2G] = meshgrid(x1,x2);
XGrid = [x1G(:),x2G(:)]; % Defines a fine grid on the plot
idx2Region = kmeans(XGrid,4,'MaxIter',1,'Start',C);
figure;
gscatter(XGrid(:,1),XGrid(:,2),idx2Region,...
    [0,0.75,0.75;0.75,0,0.75;0.75,0.75,0;0.75,0.75,0.75], '..');
hold on;
plot(Y(:,1),Y(:,2),'k*','MarkerSize',5);
title 'K-Means Data';
xlabel 'X';
ylabel 'Y';
legend('Region 1','Region 2','Region 3','Region 4','Data','Location','SouthEast');
hold off;
```



## Output:

Command Window					Command Window				
>> D									
D =									
32.4842	44.7349	78.1733	1.1332		21.4592	23.4506	44.1953	2.3400	
31.2985	28.3614	61.2225	0.1236		57.9583	49.9502	105.2711	4.5412	
39.1968	32.4856	73.1326	0.2594		16.2973	37.7318	53.0167	3.0553	
40.4226	25.1963	66.3610	0.7556		43.1487	56.9035	98.4597	3.8446	
37.7314	38.9524	78.0933	0.4815		37.0126	22.1212	59.6297	0.9537	
38.2181	23.7844	62.7371	0.7493		22.1708	16.6074	35.0543	5.1187	
46.8248	47.3781	93.8471	2.3433		42.6669	28.7091	72.2329	0.7102	
38.4742	29.9993	69.8929	0.2330		33.1804	20.4025	53.7638	1.2590	
29.9111	41.1405	72.3644	0.7139		37.7446	20.9868	58.9115	1.2279	
34.6566	49.1528	84.0819	1.8960		26.9777	29.2369	57.5834	0.3815	
36.9680	26.6371	64.8519	0.3316		25.5716	37.7943	64.6042	0.7455	
34.7824	37.7767	74.1790	0.2744		32.7680	23.3925	57.0496	0.6433	
42.5601	16.1333	56.8120	3.0824		20.4495	19.7374	37.5688	4.1285	
32.2696	40.6589	74.3550	0.5652		75.8924	78.0502	142.0791	14.1649	
22.7930	28.4175	51.8351	1.1362		53.4354	38.3760	90.9710	2.5198	
21.0189	24.6142	45.0931	2.2028		24.3427	20.0924	43.4298	2.5099	
29.3519	45.3611	75.4585	1.3871		31.6321	23.1208	55.5683	0.7205	
31.0319	56.6570	86.2696	3.7926		28.2430	30.6996	60.5166	0.2042	
38.9413	30.3953	70.7360	0.2581		30.0904	26.1960	57.5682	0.3567	
37.5992	36.4389	75.5835	0.2843		33.1226	15.3224	46.6809	3.0433	
27.6725	40.6839	69.5709	0.8220		14.4213	38.7866	51.3282	3.9557	
18.5477	27.9591	45.7980	2.4808		38.8501	37.7166	77.9664	0.4478	
30.7191	35.9912	68.4207	0.1811		47.3546	47.5959	94.4941	2.4424	
44.5659	24.8492	69.5258	1.3255		60.6838	60.5378	116.4204	6.9167	
16.1985	17.8267	26.0553	9.3919		42.9668	48.6825	91.5631	2.1513	
28.2569	13.1240	37.4437	5.1760		26.3730	30.3083	58.0572	0.4085	
24.1329	33.8676	59.1700	0.7267		50.7703	34.8382	85.3421	1.8908	
36.6691	44.9082	82.4541	1.1707		43.8412	40.2938	84.8657	1.1215	
34.6476	21.9410	57.1503	0.9087		34.3331	24.8483	60.3100	0.4290	
47.3815	44.8478	92.0849	2.0641		43.3349	36.8064	81.1046	0.8076	
22.8036	14.1878	31.4730	6.8163		22.9844	28.6173	52.2904	1.0762	
58.7501	62.6124	116.5293	7.0217		32.2176	25.7599	59.2595	0.3232	
30.6368	13.7260	41.4125	4.1955		48.8535	42.1710	90.8834	1.9766	
21.3446	30.1981	52.0043	1.3576		57.2587	45.7928	100.9798	3.8842	
37.3975	36.9200	75.8576	0.3041		27.4579	26.3764	54.9411	0.5607	
59.6276	31.6377	88.6908	3.9892		36.9716	21.4369	58.7508	1.0878	
					31.8372	27.8913	61.2571	0.1395	
					29.8452	27.2753	58.5239	0.2673	
					30.2781	17.2978	46.5067	2.4394	
					22.2145	29.5502	52.3790	1.1816	

```
>> eva
```

```
eva =
```

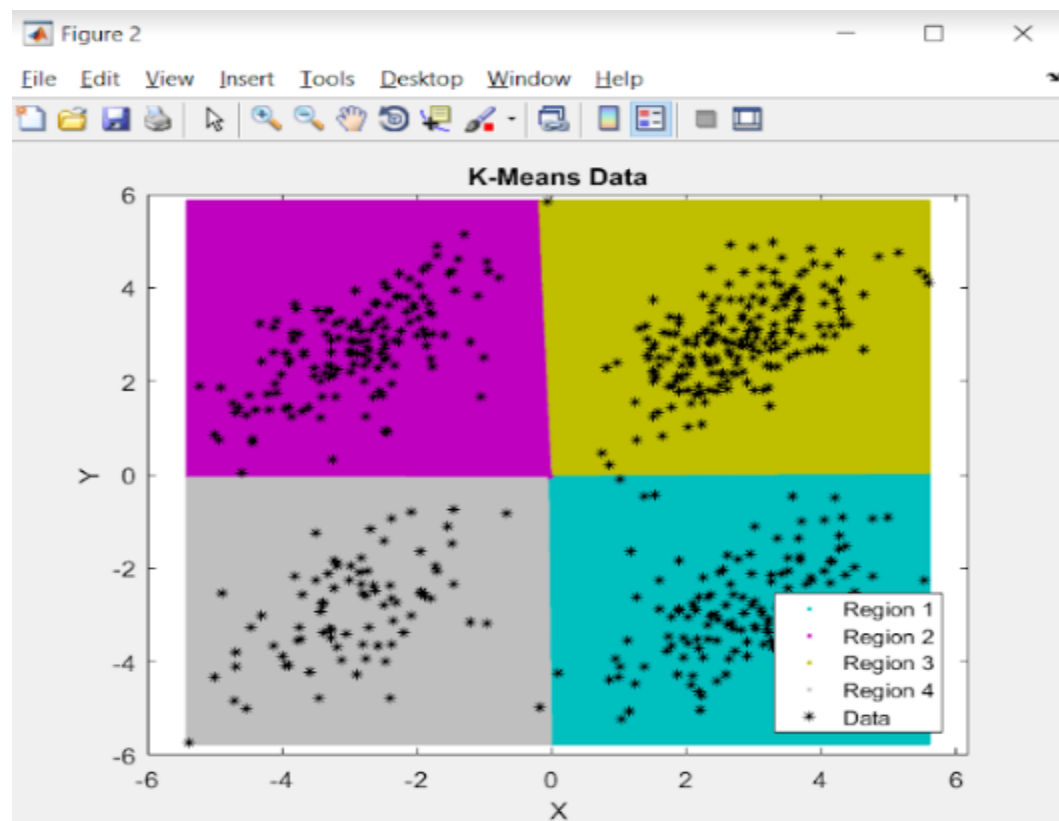
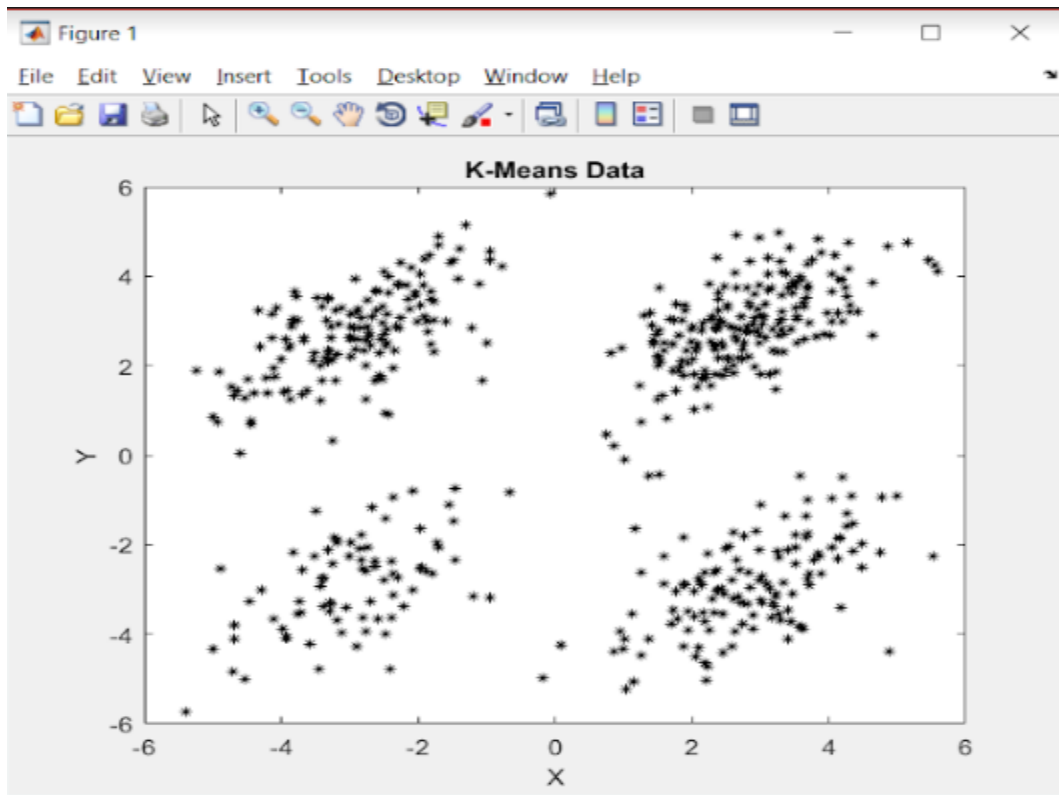
[CalinskiHarabaszEvaluation](#) with properties:

```
NumObservations: 560
```

```
InspectedK: [1 2 3 4]
```

```
CriterionValues: [NaN 477.6418 729.6816 1.4548e+03]
```

```
OptimalK: 4
```



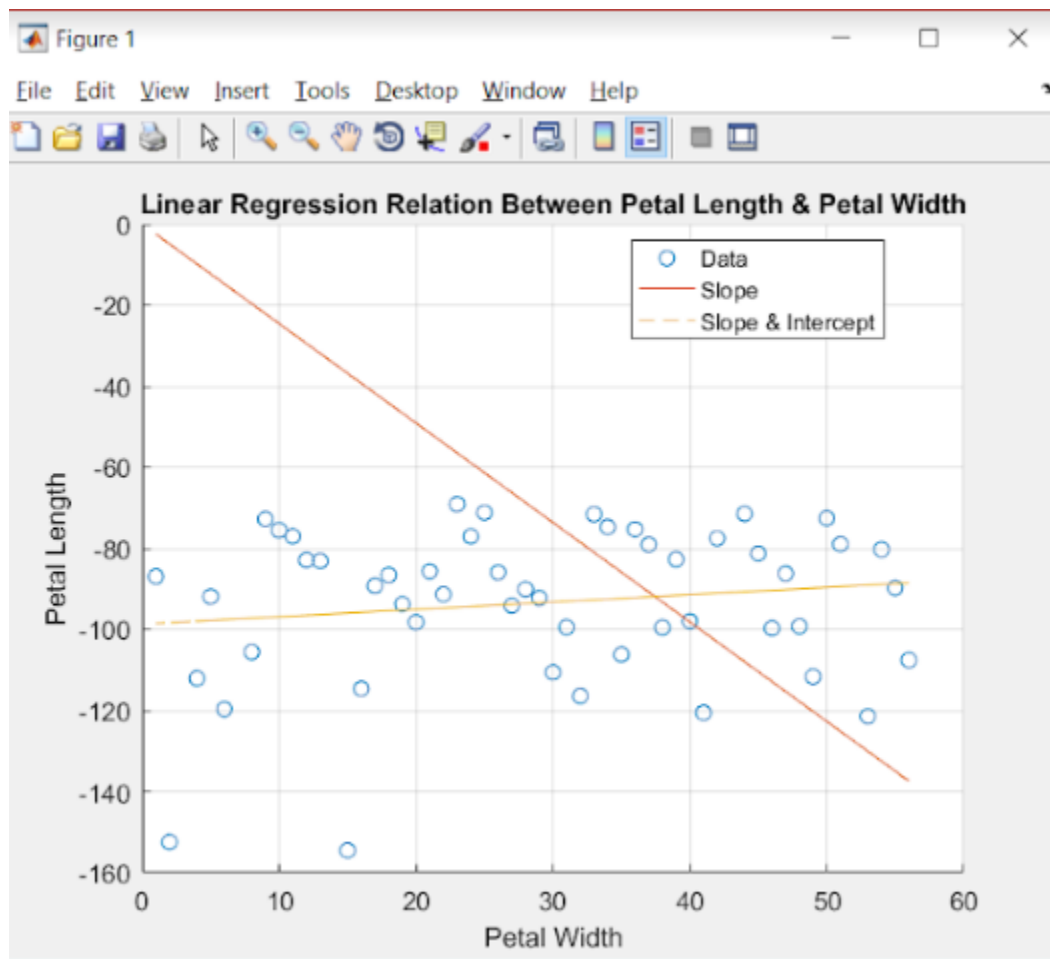
## Experiment-4

**Aim:** Implement linear regression on Iris Dataset.

**Code:**

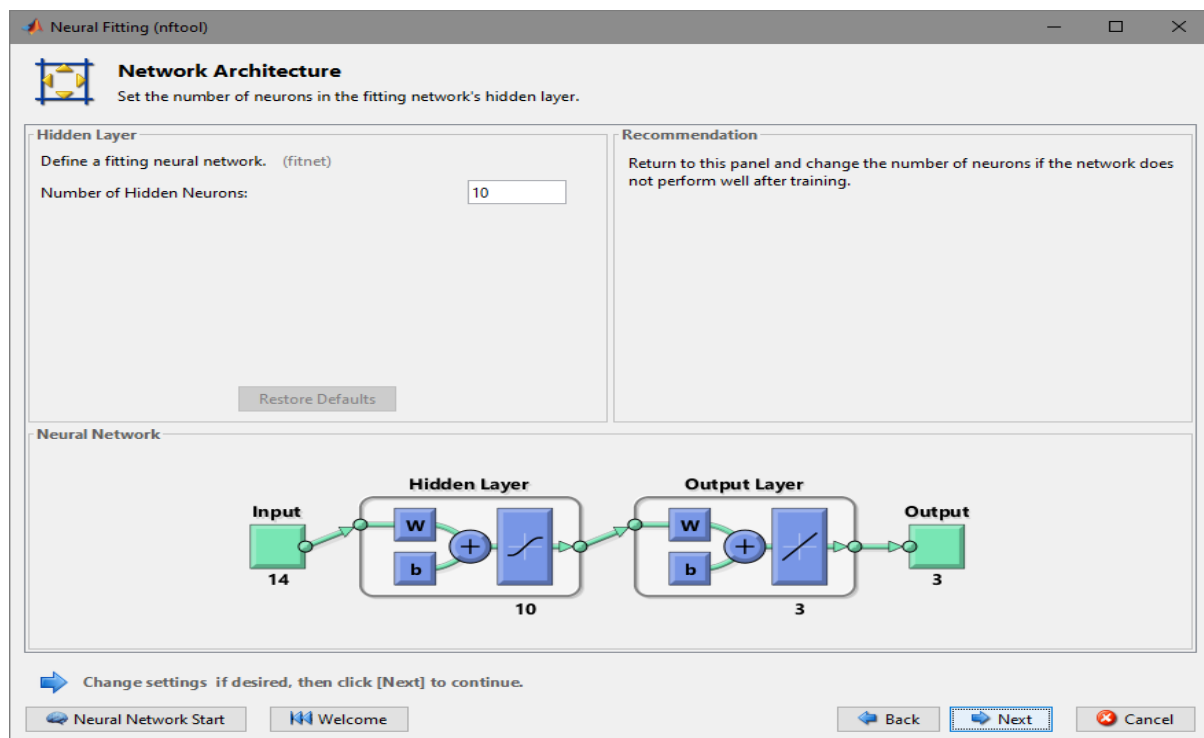
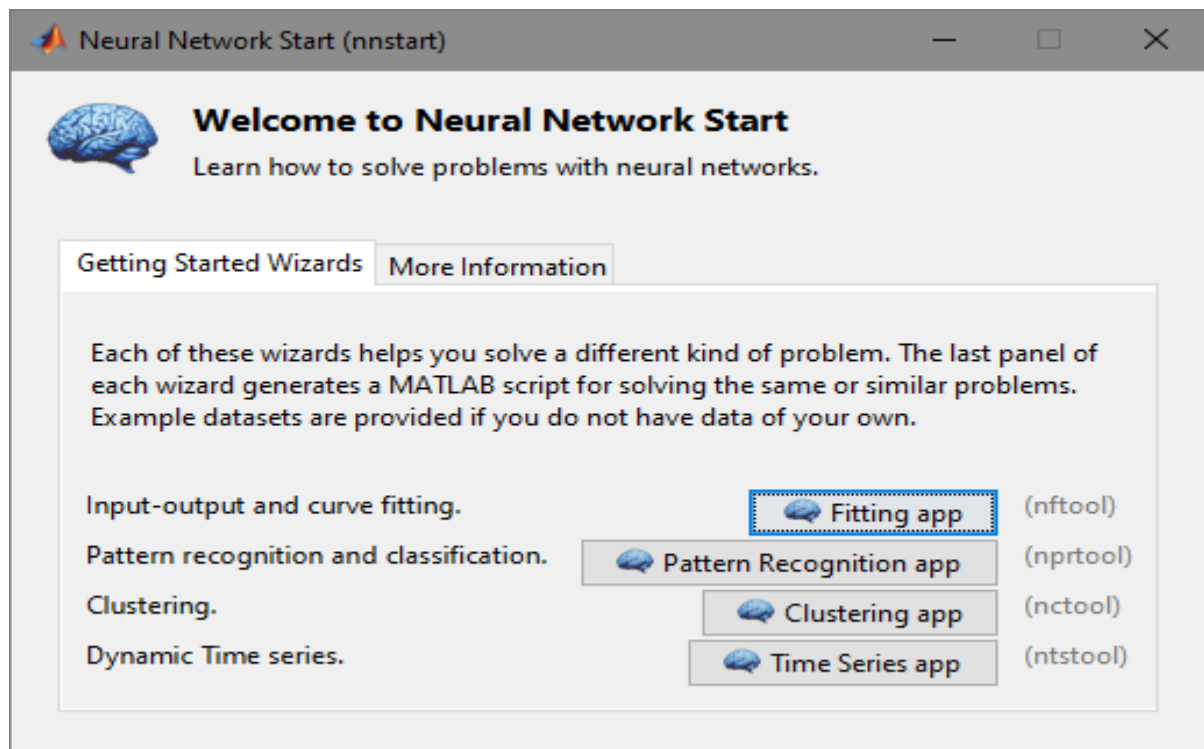
```
load fisheriris
x = hwydata(:,1);
y = hwydata(:,2);
format long
b1 = x\y
yCalc1 = b1*x;
scatter(x,y)
hold on
plot(x,yCalc1)
xlabel('Petal Width')
ylabel('Petal Length')
title('Linear Regression Relation Between Petal Length & Petal Width')
grid on
X = [ones(length(x),1) x];
b = X\y
yCalc2 = X*b;
plot(x,yCalc2,'--')
legend('Data','Slope','Slope&Intercept','Location','best');
```

**Output:**




## Experiment-5

Aim: Classify Dataset using Neural Networks.



Neural Fitting (nftool)



## Train Network

Train the network to fit the inputs and targets.

Train Network

Choose a training algorithm:

Levenberg-Marquardt

This algorithm typically requires more memory but less time. Training automatically stops when generalization stops improving, as indicated by an increase in the mean square error of the validation samples.

Train using Levenberg-Marquardt. (trainlm)

Retrain

Results

	Samples	MSE	R
Training:	2946	2.22800e-3	9.27962e-1
Validation:	631	2.35053e-3	9.22944e-1
Testing:	631	2.74236e-3	9.03759e-1

Plot Fit

Plot Error Histogram

Plot Regression

Notes

Training multiple times will generate different results due to different initial conditions and sampling.

Mean Squared Error is the average squared difference between outputs and targets. Lower values are better. Zero means no error.

Regression R Values measure the correlation between outputs and targets. An R value of 1 means a close relationship, 0 a random relationship.

Open a plot, retrain, or click [Next] to continue.

Neural Network Start


Welcome

Back

Next

Cancel

Neural Fitting (nftool)



## Evaluate Network

Optionally test network on more data, then decide if network performance is good enough.

Iterate for improved performance

Try training again if a first try did not generate good results or you require marginal improvement.

Train Again

Increase network size if retraining did not help.

Adjust Network Size

Not working? You may need to use a larger data set.

Import Larger Data Set

Optionally perform additional tests

Inputs: (none) ...

Targets: (none) ...

Samples are: ☒ Matrix columns ☐ Matrix rows

No inputs selected.

No targets selected.

Test Network

☐ MSE ☒ R

Plot Fit

Plot Error Histogram

Plot Regression

Select inputs and targets, click an improvement button, or click [Next].

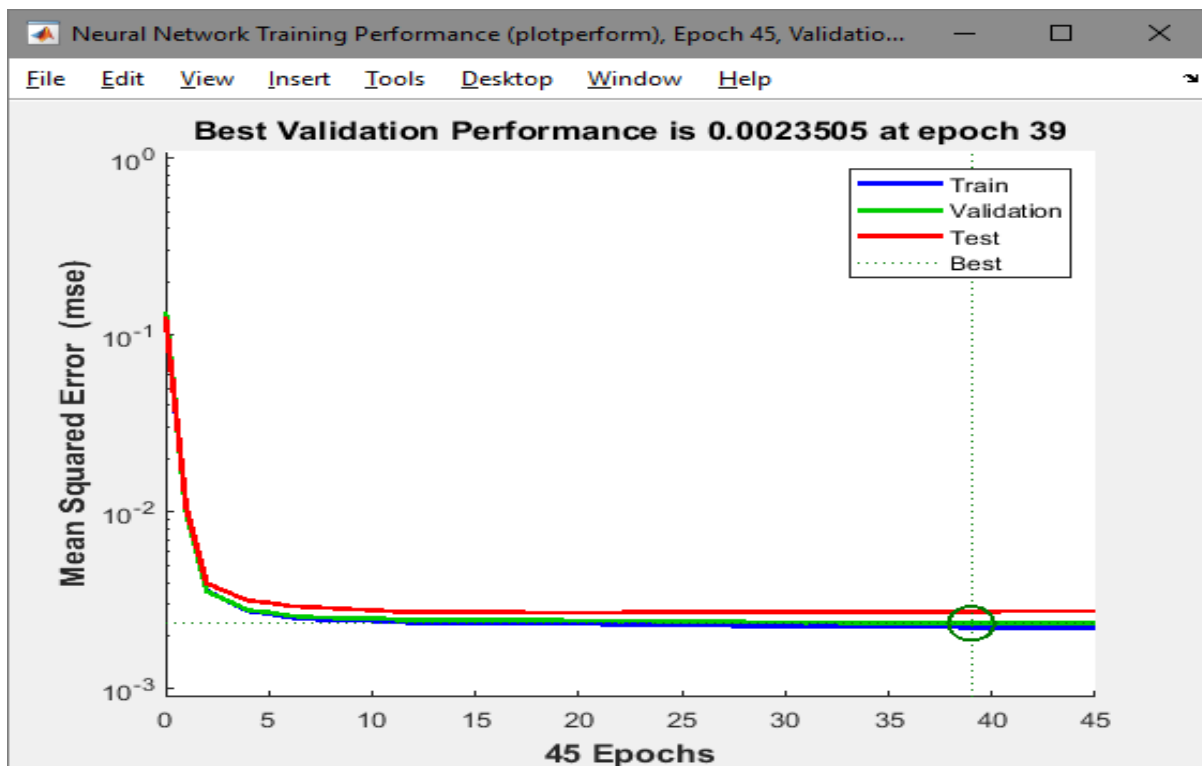
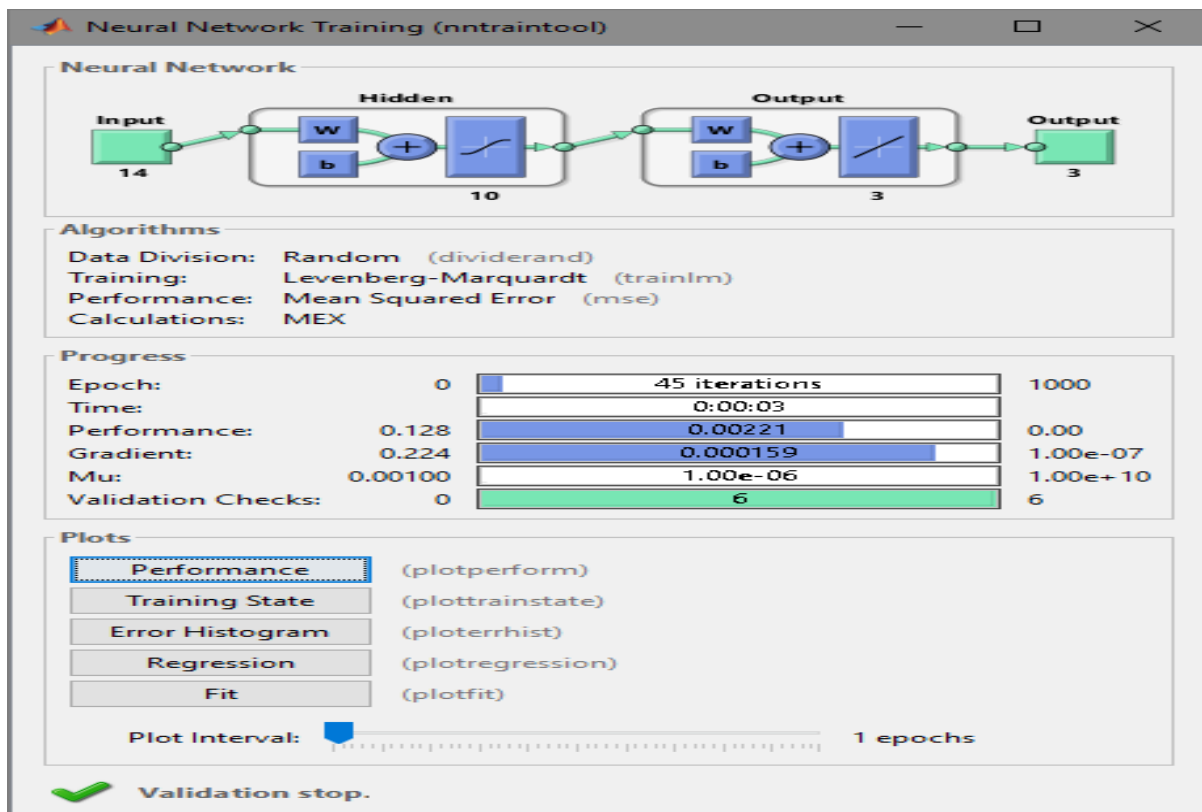
Neural Network Start

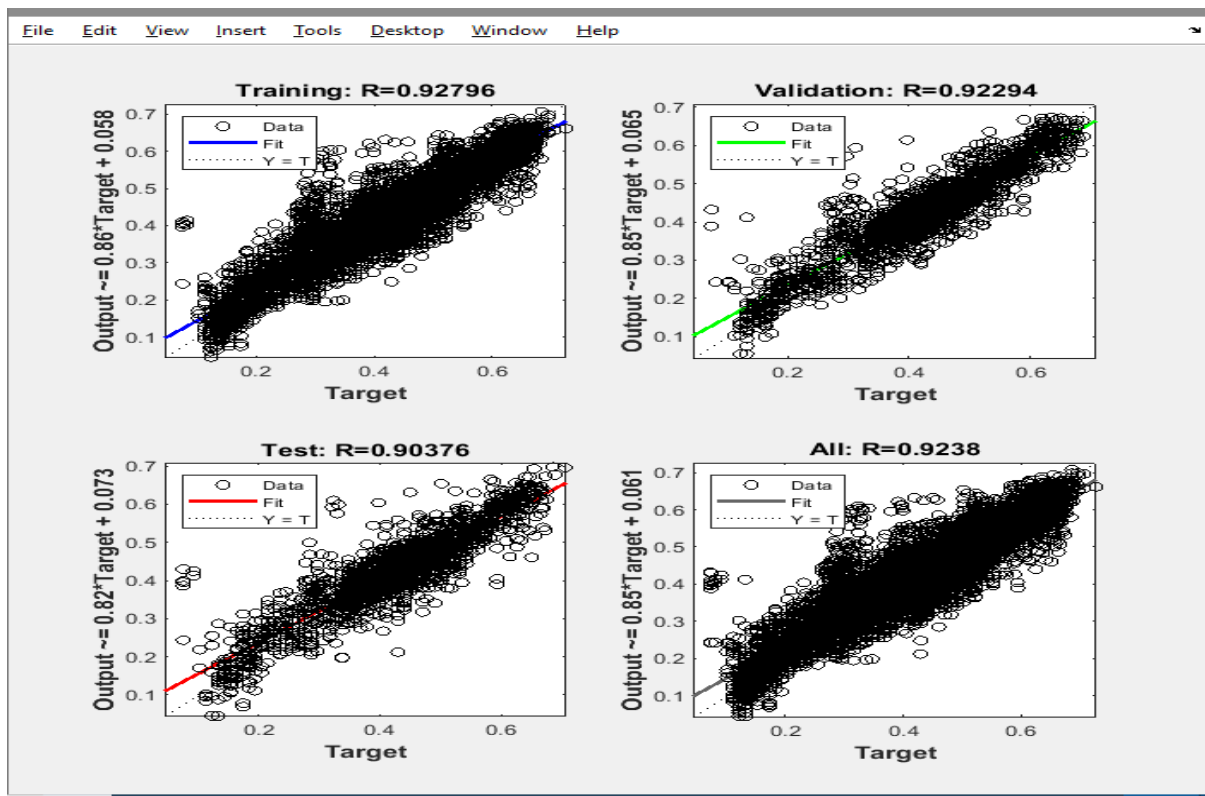
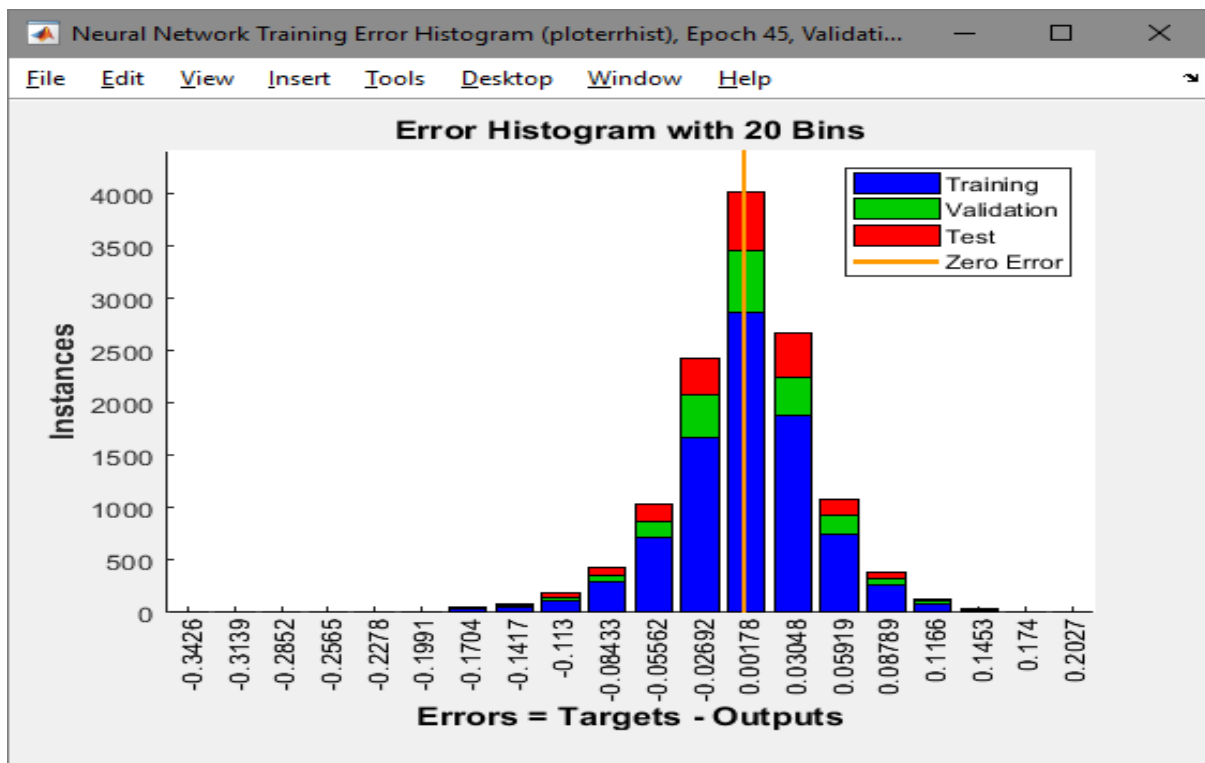
Welcome

Back

Next

Cancel







## Experiment-6

Aim: Classify Dataset by increasing number of layers and number of neurons in each layer using Neural Networks .Report classification accuracy.

Neural Fitting (nftool)

### Network Architecture

Set the number of neurons in the fitting network's hidden layer.

Hidden Layer

Define a fitting neural network. (fitnet)

Number of Hidden Neurons:

Recommendation

Return to this panel and change the number of neurons if the network does not perform well after training.

Restore Defaults

Neural Network

Change settings if desired, then click [Next] to continue.

Neural Network Start Welcome Back Next Cancel

Neural Network Training (nntraintool)

### Neural Network

### Algorithms

Data Division: Random (dividerand)  
Training: Levenberg-Marquardt (trainlm)  
Performance: Mean Squared Error (mse)  
Calculations: MEX

### Progress

Epoch:	0	55 iterations	1000
Time:		0:00:04	
Performance:	0.527	0.00213	0.00
Gradient:	0.720	5.45e-05	1.00e-07
Mu:	0.00100	1.00e-06	1.00e+10
Validation Checks:	0	6	6

### Plots


Performance (plotperform)  
Training State (plottrainstate)  
Error Histogram (ploterrhist)  
Regression (plotregression)  
Fit (plotfit)

Plot Interval: 1 epochs

Validation stop.

Stop Training Cancel

Neural Fitting (nftool)



### Train Network

Train the network to fit the inputs and targets.

Choose a training algorithm:

Levenberg-Marquardt

This algorithm typically requires more memory but less time. Training automatically stops when generalization stops improving, as indicated by an increase in the mean square error of the validation samples.

Train using Levenberg-Marquardt. (trainlm)

Retrain

#### Results


	Samples	MSE	R
Training:	2946	2.13148e-3	9.29167e-1
Validation:	631	2.35120e-3	9.23163e-1
Testing:	631	2.19186e-3	9.33220e-1


Plot Fit


Plot Error Histogram

Plot Regression

#### Notes

 Training multiple times will generate different results due to different initial conditions and sampling.

 Mean Squared Error is the average squared difference between outputs and targets. Lower values are better. Zero means no error.

 Regression R Values measure the correlation between outputs and targets. An R value of 1 means a close relationship, 0 a random relationship.

Open a plot, retrain, or click [Next] to continue.

Neural Network Start

Welcome

Back

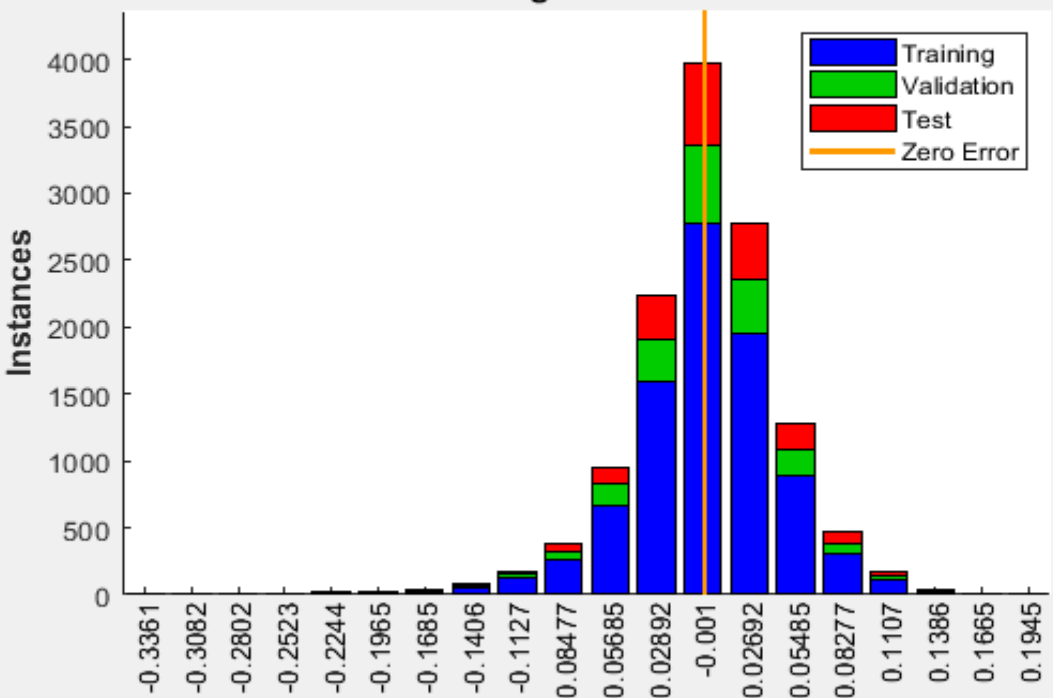
Next

Cancel

Error Histogram (ploterrhist)

File Edit View Insert Tools Desktop Window Help

### Error Histogram with 20 Bins

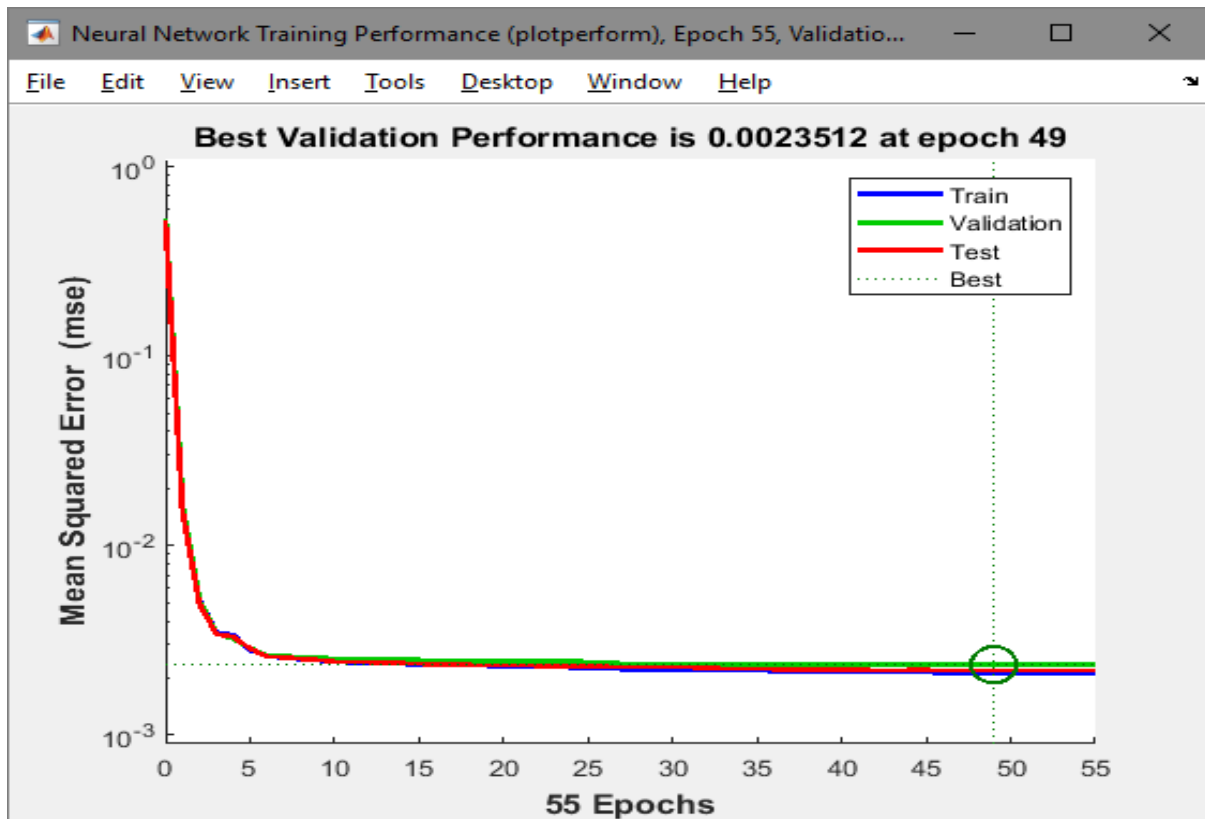
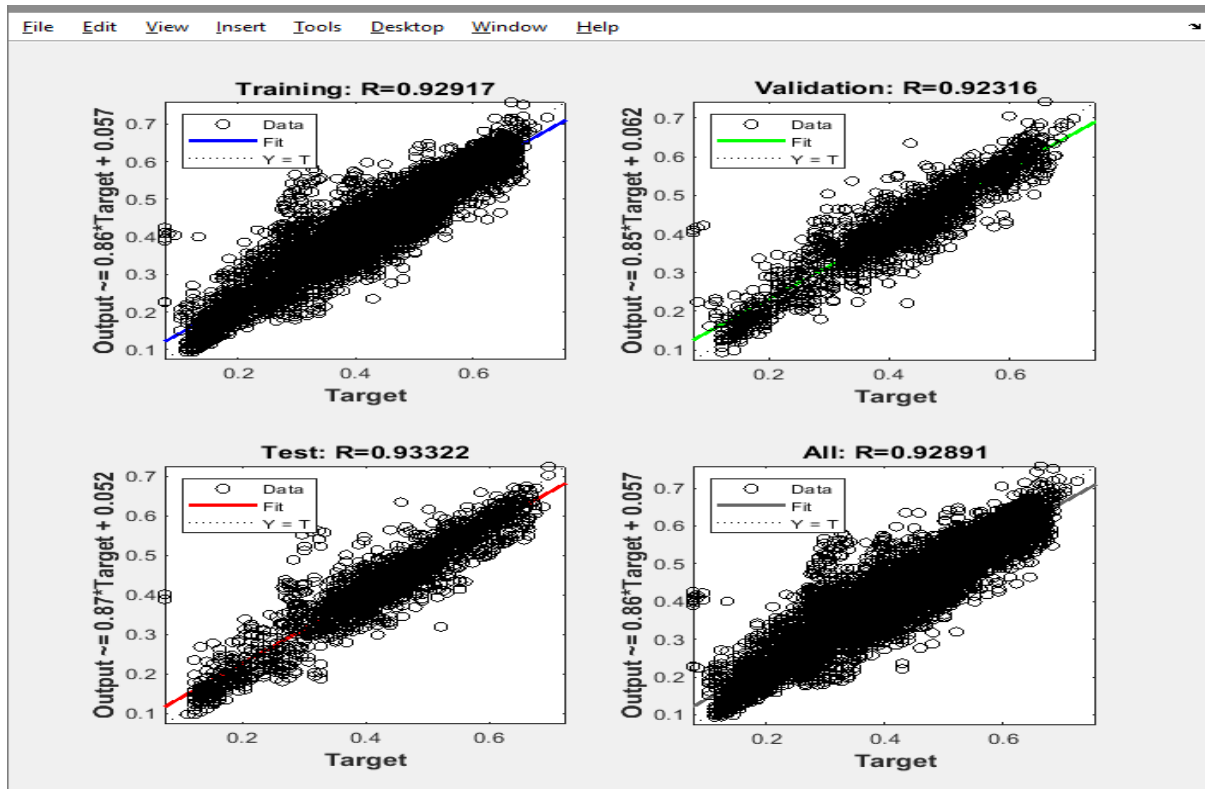


Instances

Errors = Targets - Outputs

Legend: Training (blue), Validation (green), Test (red), Zero Error (orange line)

Error Bin	Training	Validation	Test
-0.3361	0	0	0
-0.3082	0	0	0
-0.2802	0	0	0
-0.2523	0	0	0
-0.2244	0	0	0
-0.1965	0	0	0
-0.1685	0	0	0
-0.1406	0	0	0
-0.1127	0	0	0
-0.08477	0	0	0
-0.05685	0	0	0
-0.02892	0	0	0
-0.001	0	0	0
0.02692	0	0	0
0.05485	0	0	0
0.08277	0	0	0
0.1107	0	0	0
0.1386	0	0	0
0.1665	0	0	0
0.1945	0	0	0



## Experiment-7

**Aim:** Use Covertypes Dataset and implement PCA. Reduce the number of attributes to 10. Classify this data, using any two machine learning algorithms.

### Code:

```
covertypes = xlsread('covertypes.xlsx');  
[coeff,score,latent] = pca(covertypes);  
figure, biplot(coeff(:,1:2),'scores',score(:,1:2),'varlabels',  
{'v_1','v_2','v_3','v_4','v_5','v_6','v_7','v_8','v_9','v_10'})  
;  
figure, biplot(coeff(:,1:3),'scores',score(:,1:3),'varlabels',  
{'v_1','v_2','v_3','v_4','v_5','v_6','v_7','v_8','v_9','v_10'})  
;
```

### Output:

Command Window

coeff =

0.0624	-0.0454	0.2777	0.6895	0.6638	-0.0148	0.0262	0.0074	0.0057	-0.0002
0.0144	-0.0074	-0.0542	-0.6613	0.7170	0.0661	-0.2002	0.0270	-0.0160	0.0013
-0.0009	-0.0003	0.0008	-0.0000	-0.0007	0.1170	-0.0584	-0.1932	0.8905	0.3906
0.0219	0.0001	0.9501	-0.2361	-0.1538	-0.1103	-0.0670	-0.0264	0.0036	-0.0005
-0.0001	-0.0009	0.1248	-0.0463	-0.0036	0.8675	0.4251	0.2176	-0.0397	0.0016
0.9109	-0.4047	-0.0391	-0.0353	-0.0599	0.0061	-0.0050	-0.0019	-0.0008	0.0000
-0.0024	0.0010	0.0021	0.0797	-0.0724	0.0303	-0.4085	0.6600	-0.1515	0.6017
0.0040	-0.0004	-0.0053	-0.0446	0.0229	-0.2548	0.2037	0.6905	0.4132	-0.4935
0.0076	-0.0014	-0.0077	-0.1402	0.1104	-0.3887	0.7498	0.0381	-0.1071	0.4918
0.4069	0.9133	-0.0040	0.0129	0.0125	0.0027	-0.0005	-0.0004	0.0002	0.0000

```

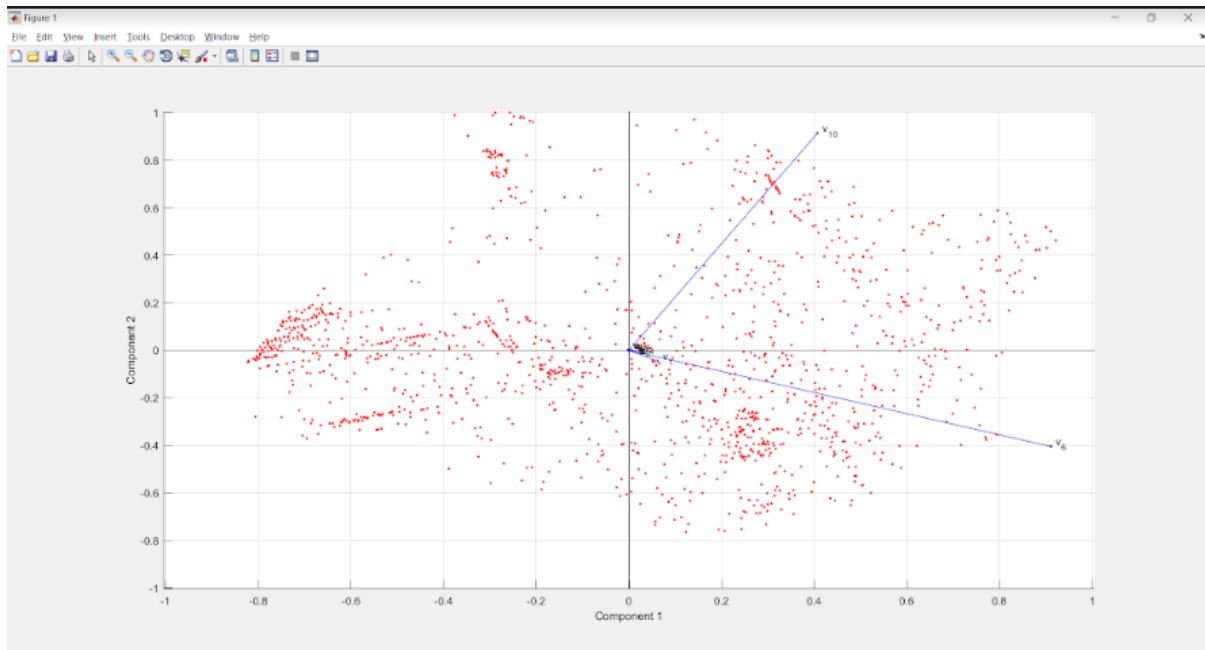
Command Window
>> score

score =

1.0e+03 *

-1.0877    4.2291    0.0316   -0.0147   -0.0535   -0.0490    0.0158    0.0009   -0.0017   -0.0008
-1.2203    4.2285   -0.0099   -0.0081   -0.0399   -0.0516    0.0192    0.0028   -0.0015   -0.0018
 1.2946    2.9942   -0.0016   -0.0285   -0.0183    0.0296    0.0031    0.0248    0.0006    0.0002
 1.2475    3.1135   -0.0226   -0.0420   -0.0109    0.0857    0.0121    0.0379    0.0069   -0.0002
-1.2421    4.1796   -0.0632    0.0158   -0.0362   -0.0411    0.0266    0.0045   -0.0020   -0.0018
-1.5912    4.1820    0.0789   -0.0752    0.0089   -0.0619   -0.0165    0.0080    0.0022   -0.0006
-0.9843    4.1579    0.0421   -0.0098   -0.0621   -0.0396    0.0084   -0.0040   -0.0002   -0.0001
-1.0511    4.1566    0.0100   -0.0040   -0.0503   -0.0380    0.0169    0.0019   -0.0017   -0.0008
-0.9592    4.1330    0.0218    0.0022   -0.0532    0.0112    0.0272    0.0052   -0.0018    0.0009
-0.9923    4.1326    0.0220   -0.0075   -0.0472   -0.0236   -0.0045   -0.0029    0.0000    0.0008
-0.9043    4.0841   -0.0486   -0.0981    0.0641    0.0070    0.0252    0.0237   -0.0020   -0.0009
 2.3493    0.2610    0.0406   -0.1026   -0.1209   -0.0094   -0.0290    0.0126    0.0032    0.0003
 1.3073    2.9555   -0.1310   -0.0341   -0.0535    0.0691   -0.0297    0.0236    0.0080   -0.0005
-0.8766    4.0595   -0.0807   -0.1047    0.0753    0.0027    0.0316    0.0229    0.0019   -0.0003
-1.2230    3.5460   -0.1848   -0.1191   -0.0279   -0.0198    0.0088    0.0164   -0.0017   -0.0009
-1.1644    3.4937   -0.2060   -0.0490   -0.1123   -0.0157    0.0165    0.0021   -0.0021    0.0007
-1.0728    4.0205   -0.1103   -0.1183    0.1200   -0.0282   -0.0037    0.0123   -0.0051   -0.0013
-1.2923    3.5844   -0.1556   -0.0513   -0.0801   -0.0156    0.0082    0.0067   -0.0015    0.0002
-1.2204    3.5146   -0.1498   -0.0234   -0.1444   -0.0326    0.0449   -0.0003   -0.0014   -0.0007
-1.1817    3.4787   -0.1628   -0.0467   -0.1214   -0.0184    0.0275    0.0025   -0.0027   -0.0005
-1.1616    3.4607   -0.1899   -0.0614   -0.0997   -0.0060    0.0027    0.0052   -0.0014    0.0007
 2.2133    0.6172   -0.1021   -0.1045   -0.0330   -0.0060    0.0185    0.0104    0.0121    0.0007
 1.3738    2.7957   -0.0853   -0.0155   -0.0689    0.0867   -0.0433    0.0161    0.0043   -0.0006
-1.2684    3.5327   -0.1215   -0.0541   -0.1063   -0.0236    0.0042   -0.0020   -0.0014   -0.0003
-1.1977    3.4631   -0.1266   -0.0417   -0.1352   -0.0175    0.0299   -0.0069   -0.0009    0.0009
-1.0992    3.3746   -0.2575   -0.1023   -0.0546   -0.0117    0.0053    0.0168   -0.0009   -0.0000
-1.1116    3.3717   -0.2315   -0.1301   -0.0401   -0.0189   -0.0012    0.0200    0.0045    0.0007
 2.6889   -0.6098   -0.0073   -0.0657   -0.1154    0.0023   -0.0430    0.0124    0.0065   -0.0000
 1.5458    2.3590   -0.0745   -0.0335   -0.0400   -0.0019    0.0111    0.0109   -0.0057   -0.0021
 1.3426    2.8762   -0.1568   -0.0179   -0.0718    0.0690   -0.0527    0.0126    0.0062   -0.0001
 1.2936    2.9964   -0.2240   -0.0232   -0.0786    0.0640   -0.0781    0.0011    0.0103   -0.0021
-1.3062    3.5492   -0.1232   -0.0776   -0.0596   -0.0215   -0.0062    0.0116   -0.0005   -0.0003
-1.2912    3.5317   -0.1206   -0.0809   -0.0647   -0.0228    0.0022    0.0118   -0.0010    0.0000
 1.2609    3.4990   -0.0941   -0.0408   -0.1281   -0.0334    0.0280   -0.0041   -0.0011   -0.0007

```



### KNN:

```
score1 = xlsread('score1.xlsx');  
Y = score1(:,11);  
%Mdl = fitcknn(score1,Y);  
Mdl = fitcknn(score1,Y,'NumNeighbors',5,'Standardize',1);
```

```
>> Mdl  
  
Mdl =  
  
    ClassificationKNN  
        ResponseName: 'Y'  
    CategoricalPredictors: []  
          ClassNames: [1 2 5]  
        ScoreTransform: 'none'  
    NumObservations: 1370  
          Distance: 'euclidean'  
        NumNeighbors: 5  
  
    Properties, Methods  
  
>> Mdl.ModelParameters  
  
ans =  
  
        NumNeighbors: 5  
          NSMethod: 'exhaustive'  
          Distance: 'euclidean'  
        BucketSize: []  
      IncludeTies: 0  
    DistanceWeight: 'equal'  
      BreakTies: 'smallest'  
        Exponent: []  
           Cov: []  
          Scale: []  
StandardizeData: 1  
        Version: 1  
        Method: 'KNN'  
          Type: 'classification'
```

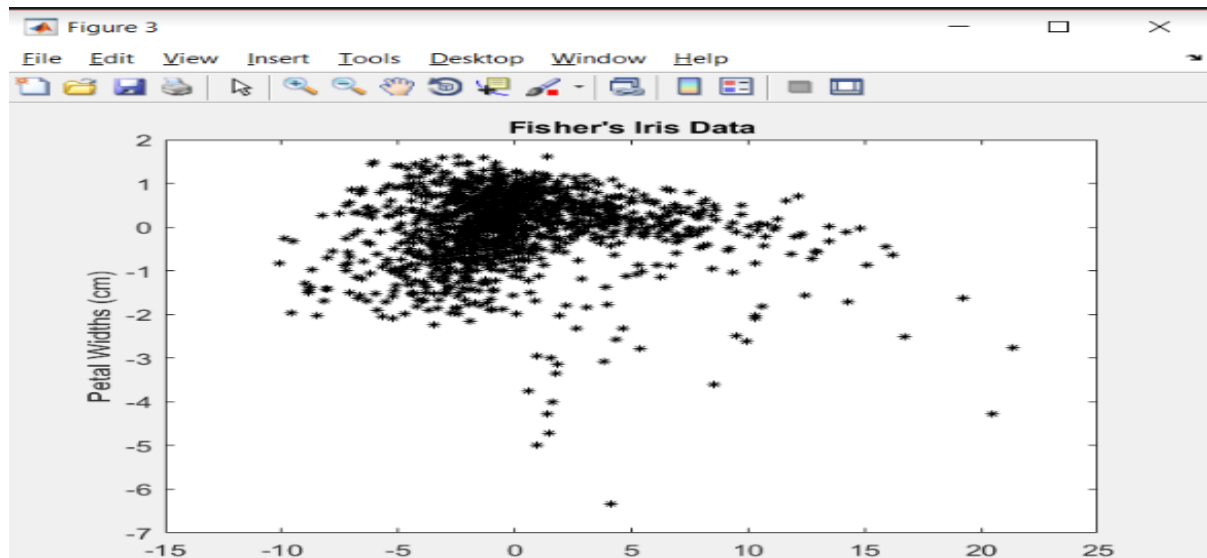
### Kmeans

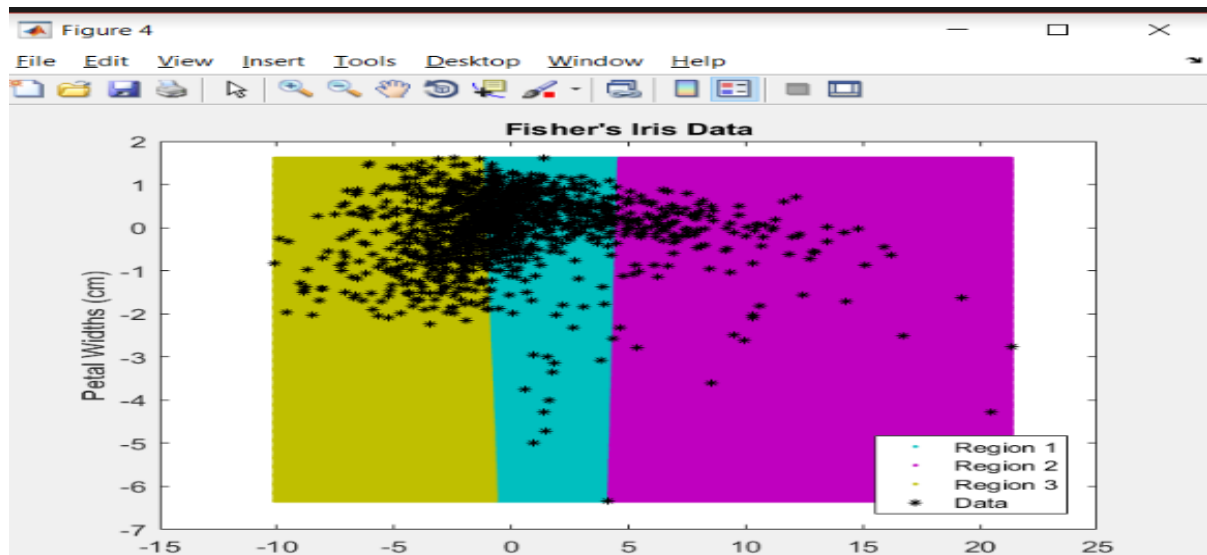
```
X = score(:,9:10);  
figure;  
plot(X(:,1),X(:,2),'k*','MarkerSize',5);  
title 'CoverType Data';  
rng(1); % For reproducibility  
[idx,C,sumD,D] = kmeans(X,3);  
x1 = min(X(:,1)):0.01:max(X(:,1));  
x2 = min(X(:,2)):0.01:max(X(:,2));
```

```

[x1G,x2G] = meshgrid(x1,x2);
XGrid = [x1G(:),x2G(:)]; % Defines a fine grid on the plot
idx2Region = kmeans(XGrid,3,'MaxIter',1,'Start',C);
figure;
gscatter(XGrid(:,1),XGrid(:,2),idx2Region,...
    [0,0.75,0.75;0.75,0,0.75;0.75,0.75,0],'.');
hold on;
plot(X(:,1),X(:,2),'k*','MarkerSize',5);
title 'CoverType Data';
legend('Region 1','Region 2','Region
3','Data','Location','SouthEast');
hold off;

```





## Experiment-8

**Aim:** Classify dataset using SVM's.

**Code:**

```
% SVM Linear classification
% A 2-feature example

clear all; close all;

% Load training features and labels
[y, x] = libsvmread('twofeature.txt');

% Set the cost
C = 100;

% Train the model and get the primal variables w, b from the
model
% Libsvm options
% -s 0 : classification
% -t 0 : linear kernel
% -c somenumber : set the cost
model = svmtrain(y, x, sprintf('-s 0 -t 0 -c %g', C));
w = model.SVs' * model.sv_coef;
b = -model.rho;
if (model.Label(1) == -1)
    w = -w; b = -b;
```



```
end
```

```
% Plot the data points
figure
pos = find(y == 1);
neg = find(y == -1);
plot(x(pos,1), x(pos,2), 'ko', 'MarkerFaceColor', 'b'); hold on;
plot(x(neg,1), x(neg,2), 'ko', 'MarkerFaceColor', 'g')

% Plot the decision boundary
plot_x = linspace(min(x(:,1)), max(x(:,1)), 30);
plot_y = (-1/w(2))*(w(1)*plot_x + b);
plot(plot_x, plot_y, 'k-', 'LineWidth', 2)

title(sprintf('SVM Linear Classifier with C = %g', C),
'FontSize', 14)
```

## Output:

