CHAPTER 7

DISCUSSION OF RESULTS AND CONCLUSION

7.1 INTRODUCTION

This research work proposed computationally efficient eager and lazy learning associative classification methods. In this chapter, the results of the proposed methods are compared and discussed based on accuracy, number of rules generated, number of rules used in the classifier, computation time, sensitivity, specificity, precision and recall. This chapter also concludes the research work.

7.2 COMPARISON OF DATASETS

Twelve benchmark datasets are used in this research work for evaluation and description of the dataset is given in Section 1.4. Figure 7.1 shows the color representation of the various associative classification methods discussed in this chapter.

<table>
<thead>
<tr>
<th>Color</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Purple</td>
<td>Traditional classifier - Decision Tree</td>
</tr>
<tr>
<td>Yellow</td>
<td>Traditional associative classifier – CBA</td>
</tr>
<tr>
<td>Blue</td>
<td>Existing System</td>
</tr>
<tr>
<td>Orange</td>
<td>Proposed System</td>
</tr>
</tbody>
</table>

Figure 7.1 Color Descriptions for Various Methods
Each dataset is compared using following four parameters. Description of these parameters is discussed in Section 1.5.

1. Accuracy.
2. Number of rules generated.
3. Number of rules used in the classifier.
5. Sensitivity and specificity
6. Precision and recall

### 7.2.1 Comparison for Balance Scale Dataset

This dataset includes 625 instances, described by 5 attributes and 3 class values.

![Accuracy Comparison for Balance Scale dataset](image)

**Figure 7.2 Accuracy Comparison for Balance Scale Dataset**

Figure 7.2 depicts the accuracy comparison for Balance Scale dataset. CAC has the classification accuracy of 90.3%. This is 0.89 % improved accuracy over the best conventional method, L3 algorithm.
Figure 7.3 Number of Rules Generated for Balance Scale Dataset

Figure 7.3 shows the number of rules generated for Balance Scale dataset by different associative classification methods. Total number of rules generated by CAC is lesser when compared to all the other eager methods. CBA, GNP - RAC, GNP – IG AC, GARC and CWAC generated 2.21, 2.19, 1.9, 1.65 and 1.5 times more rules respectively when compared with CAC.

Figure 7.4 Number of Rules Used in the Classifier for Balance Scale Dataset
Figure 7.4 shows the number of rules used in the classifier for Balance Scale dataset. Both CAC and L3 used 4 rules in the classifier whereas GARC and CWAC used 1.5 times more rules when compared to CAC. GNP - RAC and GNP - IG AC used 67 and 52 rules which are 16.75 and 13 times more number of rules respectively when compared to CAC. CAC generated less number of rules and holds the highest classification accuracy.

Figure 7.5 Total Computation Time for Balance Scale Dataset

Figure 7.5 shows total computation time for Balance Scale dataset. The computation time for CAC method is 0.04 seconds whereas the existing L3 algorithm took 0.08 seconds which is twice the time taken by CAC. The computation time of both CWAC and GRAC were 0.09.

GNP – IG with Lift measure (with Mutation - II) took lesser time when compared with other GNP methods. However, this is 174.5 times more when compared with CAC.

In lazy learning associative classification, CHiSC method took lesser time. However, this time is 27.25 times more than that of CAC method. For Balance Scale dataset, CAC provided high classification accuracy, generated minimal number of rules and has less computation time.
7.2.2 Comparison for Breast Cancer Dataset

This data set includes 286 instances with two class labels and described by 10 attributes.

![Accuracy Comparison for Breast Cancer dataset](image)

**Figure 7.6 Accuracy Comparison for Breast Cancer Dataset**

Figure 7.6 shows the accuracy comparison for Breast Cancer dataset. Compact Highest Subset Confidence (CHiSC) holds the highest classification accuracy of 85.22%. This accuracy is 3.99% improvement over L3 algorithm.

![No. of rules generated for Breast Cancer dataset](image)

**Figure 7.7 Number of Rules Generated for Breast Cancer Dataset**
Figure 7.7 shows the number of rules generated for Breast Cancer dataset. CWAC generated less number of rules but it was slightly more than GARC but gave higher classification accuracy than GARC.

![Bar chart showing the number of rules generated for different methods.](image)

**Figure 7.8 Number of Rules Used in the Classifier for Breast Cancer Dataset**

Figure 7.8 shows the number of rules used in the classifier for Breast Cancer dataset. CWAC used 20 rules for classification whereas the existing GNP random method used 714 rules, which is about 59.5 times as CWAC.

![Bar chart showing the total computation time for different methods.](image)

**Figure 7.9 Total Computation Time for Breast Cancer Dataset**

Figure 7.9 shows the total computation time for Breast Cancer dataset. CHiSC method has the less total computation time. Considering the eager methods, CAC has less computation time. This is 1.4 times as CHiSC. Since the dataset has 10 attributes, the training time is more for CAC and CWAC. So, for Breast Cancer dataset CHiSC has highest classification accuracy and less computation time.
7.2.3 Comparison for Breast – W Dataset

This data set includes 699 instances and 2 class values. The instances are described by 10 attributes.

![Accuracy Comparison for Breast - W Dataset](image)

**Figure 7.10 Accuracy Comparison for Breast - W Dataset**

Figure 7.10 depicts the accuracy comparison for Balance - W dataset. GNP-IG with Lift measure (Mutation - II) holds the highest classification accuracy of 98.28 % when compared with the other proposed methods. However, this accuracy is 0.26% lower when compared with existing GARC.

![No. of rules generated for Breast-w dataset](image)

**Figure 7.11 Number of Rules Generated for Breast – W Dataset**

Figure 7.11 shows the number of rules generated for Breast - W dataset. CWAC generated less number of rules when compared to all other eager methods.
GARC generated one rule more than CWAC. CAC, GNP - IG AC and CBA generated 5.38, 6.73 and 8.49 times more rules respectively when compared to CWAC.

![Graph](image)

**Figure 7.12 Number of Rules Used in the Classifier for Breast –W Dataset**

Figure 7.12 shows the number of rules used in the classifier for Breast –W dataset. CAC and L3 used 7 rules for classification. GARC and CWAC used 8 rules for classification whereas the GNP – IG AC used 24 rules and GNP random used 137 rules which are 3.42 and 19.57 times more as CAC method respectively.

![Graph](image)

**Figure 7.13 Total Computation Time for Breast –W Dataset**
Figure 7.13 shows the total computation time for Breast – W dataset. CHiSC method has the less computation time. Considering the eager methods, CAC has less computation time but it is 1.18 times more as CHiSC method. Since the dataset has 10 attributes, the training time is more for CAC and CWAC.

### 7.2.4 Comparison for Car Dataset

This data set contains 1728 instances with 4 class values. The instances are described by 7 attributes.

![Accuracy Comparison for Car dataset](image)

**Figure 7.14 Accuracy Comparison for Car Dataset**

Figure 7.14 depicts accuracy comparison for Car dataset. CWAC holds the highest classification accuracy of 81.57% when compared with the other proposed methods. However, this accuracy is 6.93% lower when compared with existing GARC.
Figure 7.15 Number of Rules Generated for Car Dataset

Figure 7.15 shows the number of rules generated for Car dataset. CWAC generated minimum number of rules when compared with all the other eager methods.

Figure 7.16 Number of Rules Used in the Classifier for Car Dataset

Figure 7.16 shows the number of rules used in the classifier for Car dataset. Both CWAC and GARC methods used only 27 rules for classification. The CAC method used 29 rules while GNP IG method used 8.51 times more rules when compared to the CWAC.
Figure 7.17 Total Computation Time for Car Dataset

Figure 7.17 shows total computation time for Car dataset. Car dataset consists of 7 attributes and number of transaction is also more. So GARC method has the lowest total computation time but CHiSC took only 0.0024 seconds to predict the single instance.

7.2.5 Comparison for Credit – a Dataset

This data set includes 690 instances with 2 classes. The instances are described by 16 attributes.

Figure 7.18 Accuracy Comparison for Credit – a Dataset
Figure 7.18 depicts the accuracy comparison for Credit dataset. The CHiSC has the classification accuracy of 83.33%. It has improved the accuracy about a percent when compared to the best conventional method, L3 algorithm.

Figure 7.19 Number of Rules Generated for Credit – a Dataset

Figure 7.19 shows the number of rules generated for Credit - a dataset. CWAC generated less number of rules compared with other eager methods. CBA method generates 9.79 times, GNP IG method generates 10.28 times, and CAC method generates 5.81 times more rules when compared to CWAC method. GARC method generated less number of rules in the existing system but it generates 293 more rules than the CWAC method.

Figure 7.20 Number of Rules Used in the Classifier for Credit – a Dataset
Figure 7.20 shows the number of rules used in the classifier for Credit - a dataset. In the proposed system, CWAC method used minimum number of rules in the classifier but it is more than GARC by one rule. CAC and GNP IG used slightly more number of rules than GARC.

![Total Computation Time for Credit - a dataset](image)

**Figure 7.21 Total Computation Time for Credit – a Dataset**

Figure 7.21 shows the computation time for Credit -a dataset. CHiSC method has the lowest computation time of 2.11 seconds. In the eager methods, GARC had the lowest computation time but it took 32.4 seconds more than CHiSC. Credit – a dataset consists of 16 attributes and number of rules generated by the CAC and CWAC are more, so training time was high for CAC and CWAC method compared with CHiSC. CHiSC also had the highest classification accuracy for this dataset.

In GNP based methods, GNP – IG – Chi-square measure with Mutation-I has the lowest computation time but it took 90.19 more seconds when compared to CHiSC method.

### 7.2.6 Comparison for Diabetes Dataset

This data set has 768 instances with 2 classes. The instances are described by 9 attributes.
**Figure 7.22 Accuracy Comparison for Diabetes Dataset**

Figure 7.22 depicts the accuracy comparison for Diabetes dataset. The GNP – IG Mutation - I with Lift measure has the classification accuracy of 87.92%. It has 9.62% improved classification accuracy when compared to the best conventional method, L3 algorithm.

**Figure 7.23 Number of Rules Generated for Diabetes Dataset**

Figure 7.23 shows the number of rules generated for Diabetes dataset. CWAC generated less number of rules when compared to all other eager associative classification methods.
Figure 7.24 Number of Rules Used in the classifier for Diabetes Dataset

Figure 7.24 shows the number of rules used in the classifier for Diabetes dataset. In the proposed system, CWAC method used minimum number of rules in the classifier but it used 2 more rules than GARC. GNP - IG AC, and CAC used slightly more number of rules than CWAC.

Figure 7.25 Total Computation Time for Diabetes Dataset

Figure 7.25 shows the total computation time for Diabetes dataset. CAC has less computation time.
7.2.7 Comparison for Ecoli Dataset

This data set includes 336 instances with 8 attributes and 8 class values.

![Accuracy Comparison for Ecoli dataset](image)

**Figure 7.26 Accuracy Comparison for Ecoli Dataset**

Figure 7.26 depicts the accuracy comparison for Ecoli dataset. CAC holds the highest classification accuracy of 85.88%. It has 7.9% improved accuracy when compared to the traditional classifier, decision tree.

![No. of rules generated for Ecoli dataset](image)

**Figure 7.27 Number of Rules Generated for Ecoli Dataset**

Figure 7.27 shows the number of rules generated for Ecoli dataset. CAC generated less number of rules when compared to all other eager associative
classification methods. GARC, CWAC and GNP-IG generated 1.52, 1.26 and 5.07 times more rules when compared to CAC method.

**Figure 7.28 Number of Rules Used in the Classifier for Ecoli Dataset**

Figure 7.28 shows the number of rules used in the classifier for Ecoli dataset. CAC, CWAC and L3 used 10 rules in the classifier but CAC has higher classification accuracy than L3 and CWAC. The GNP –IG method uses 2.2 times more rules when compared to the CAC method.

**Figure 7.29 Total Computation Time for Ecoli Dataset**
Figure 7.29 shows total computation time for Ecoli dataset. CAC method has the less computation time of 0.11 seconds. In the conventional methods, L3 has the lowest computation time but it took about 0.01 more seconds than CAC.

In GNP based methods, GNP – IG AC - Lift measure with Mutation - I has the lowest computation time but it took about 37.72 times more computation time as CAC method. In lazy learning methods, CHiSP method has lower computation time of 1.38 seconds but the computation time was 12.55 times as CAC method.

7.2.8 Comparison for Flare Dataset

This data set includes 1389 instances with 13 attributes and 6 class values.

![Accuracy Comparison for Flare dataset](image)

**Figure 7.30 Accuracy Comparison for Flare Dataset**

Figure 7.30 depicts the accuracy comparison for Flare dataset. GNP – IG AC – Lift measure with Mutation-II holds the highest classification accuracy of 86.61% when compared with other proposed methods. However, this accuracy is 1.93% lower when compared with L3.
Figure 7.31 Number of Rules Generated for Flare Dataset

Figure 7.31 shows the number of rules generated for Flare dataset. CWAC generated less number of rules when compared to all other eager associative classification methods. GARC generated 4 more rules than the CWAC method. CBA, GNP RAC and CAC methods generates 2.46, 2.17, and 1.31 times more rules respectively when compared to CWAC method.

Figure 7.32 Number of Rules Used in the Classifier for Flare Dataset
Figure 7.32 shows the number of rules used in the classifier for Flare dataset. CWAC used 2 rules more than GARC and provided higher classification accuracy. CAC and GNP-IG used 2 and 4.37 times more rules respectively than the CWAC.

![Total Computation Time for Flare Dataset](chart.png)

**Figure 7.33 Total Computation Time for Flare Dataset**

Figure 7.33 shows the total computation time for Flare dataset. CWAC method has the less computation time of 1.16 seconds. In the conventional methods, GARC has less computation time but it took about 0.1 seconds more than CWAC.

In GNP based methods, GNP – IG – Lift measure with Mutation - II has less computation time but it took about 28.87 times more computation time as CWAC method. In lazy learning methods, CHiSC method has less computation time of 3.31 seconds but the computation time was 2.85 times as CWAC method. Flare dataset consists of 13 attributes with 6 class values as well as CAC and CWAC generated less number of rules. So lazy learning methods needs more computation time compared with CWAC and CAC.
7.2.9 Comparison for Glass Dataset

This data set includes 214 instances with 10 attributes and 6 class values.

![Accuracy Comparison for Glass dataset](image)

**Figure 7.34 Accuracy Comparison for Glass Dataset**

Figure 7.34 depicts the accuracy comparison for Glass dataset. In eager associative classification method, GNP-IG-Lift measure with Mutation-II has the highest classification accuracy of 82.85%. This is 20.95% and 10.25% improved accuracy over the best conventional methods, GARC and L3 algorithm respectively.

![No. of rules generated for Glass dataset](image)

**Figure 7.35 Number of Rules Generated for Glass Dataset**
Figure 7.35 shows the number of rules generated for Glass dataset. CWAC generated less number of rules compared to all other eager associative classification methods. GARC generated 56 more rules than CWAC method. CBA, GNP random, GNP IG and CAC methods generated 5.71, 5.52, 5.11, and 3.11 times more rules respectively when compared to CWAC method.

![Graph showing number of rules used in the classifier for Glass dataset](image)

**Figure 7.36 Number of Rules Used in the Classifier for Glass Dataset**

Figure 7.36 shows the number of rules used in the classifier for Glass dataset. CAC and L3 used only 5 rules in the classifier i.e., it used only 0.2% generated rules in the classifier. CWAC and GNP-IG used 4.4 and 9.2 times more rules respectively in the classifier than CAC.

![Graph showing total computation time for Glass dataset](image)

**Figure 7.37 Total Computation Time for Glass Dataset**
Figure 7.37 shows total computation time for Glass dataset. CAC has less computation time of 0.56 seconds. In the conventional methods, L3 has less computation time but it took 0.07 seconds more than CAC.

In GNP based methods, GNP – IG – Chi-square measure with Mutation-II has less computation time but it took 8.84 times more computation time as CAC method. In lazy learning methods, CHiSP method has less computation time of 1.02 seconds but the computation time is 1.82 times as CAC method.

Glass dataset consists of 10 attributes but it has 6 class attributes as well as CAC and CWAC generates lesser number of rules. So lazy learning methods needs more computation time compared with CWAC and CAC.

7.2.10 Comparison for Ionosphere Dataset

This data set includes 351 instances with 35 attributes and 6 class values.

![Accuracy Comparison for Ionosphere dataset]

**Figure 7.38 Accuracy Comparison for Ionosphere Dataset**

Figure 7.38 depicts the accuracy comparison for Ionosphere dataset. CHiSC method has the classification accuracy of 96.29%. This is 4.29% improved accuracy over the best conventional methods, L3 algorithm.
Figure 7.39 Number of Rules Generated for Ionosphere Dataset

Figure 7.39 shows the number of rules generated for Ionosphere dataset. CWAC generated less number of rules compared to all other eager associative classification methods. GARC generates 62 more rules, than the CWAC method. CBA method, GNP random, GNP IG and CAC methods generates 22.11, 19.42, 19.41 and 20.01 times more rules respectively when compared to CWAC method.

Figure 7.40 Number of Rules Used in the Classifier for Ionosphere Dataset

Figure 7.40 shows the number of rules used in the classifier for Ionosphere dataset. CAC and L3 methods used 34 and 36 rules in the classifier respectively. CWAC and GNP-IG used 2.3 and 2.72 times more rules in the classifier respectively than CAC.
Figure 7.41 Total Computation Time for Ionosphere Dataset

Figure 7.41 shows total computation time for Ionosphere dataset. CHiSC method has less total computation time of 1.72 seconds. In the eager associative classification method, GARC has less computation time but it took 12.69 times more computation time as CHiSC. This dataset consists of 35 attributes and CAC and CWAC generates 74587 and 3788 class association rules. So more training time is needed CAC and CWAC compared with CHiSC.

In GNP based methods, GNP – IG – Lift measure with Mutation - II has less computation time but it took 16.08 times more computation time as CHiSC method.

7.2.11 Comparison for Iris Dataset

This data set contains 3 classes of 50 instances each, where each class refers to a type of iris plant.

Figure 7.42 Accuracy Comparison for Iris Dataset
Figure 7.42 depicts the accuracy comparison for Iris dataset. HiSC has the highest classification accuracy of 96.67%. This is little bit improvement over the conventional methods.

![No. of rules generated for Iris dataset](image)

**Figure 7.43 Number of Rules Generated for Iris Dataset**

Figure 7.43 shows the number of rules generated for Iris dataset. CAC generated less number of rule compared to all other eager associative classification methods. GARC, CBA, GNP RAC, GNP IG AC and CWAC generated 2, 3.23, 6.9, 5.97 and 1.86 times more rules respectively when compared to CAC method.

![No. of rules used in the classifier for Iris dataset](image)

**Figure 7.44 Number of Rules Used in the Classifier for Iris Dataset**
Figure 7.44 shows the number of rules used in the classifier for Iris dataset. CAC, CWAC and GARC methods used only 7 rules in the classifier but CAC has the highest classification accuracy than GARC and CWAC.

![Total Computation Time for Iris dataset](image)

**Figure 7.45 Total Computation Time for Iris Dataset**

Figure 7.45 shows total computation time for Iris dataset. CAC method has the lowest total computation time of 0.06 seconds. In GNP based methods, GNP – IG – Lift measure with Mutation - II has the lowest computation time but it took about 39.33 times more computation time as CAC. In lazy learning associative classification CHiSP has lowest computation time but it took 14.33 times more computation time as CAC.

7.2.12 Comparison for Mushroom

This data set includes 8124 instances with 23 attributes and 2 class values.

![Accuracy Comparison for Mushroom dataset](image)

**Figure 7.46 Accuracy Comparison for Mushroom Dataset**
Figure 7.46 depicts the comparison of accuracy for Mushroom dataset. CHiSP and CHiSC methods have the highest classification accuracy of 98.52%. This is 0.52% improved accuracy over the best conventional methods, L3 algorithm.

![No. of rules generated for Mushroom dataset](image)

**Figure 7.47 Number of Rules Generated for Mushroom Dataset**

Figure 7.47 shows the number of rules generated for Mushroom dataset. CWAC generated less number of rules compared to all other eager associative classification methods. GARC generates 72 more rules, than the CWAC method. CBA, GNP - RAC, GNP - IG AC and CAC methods generated 19.51, 18.97, 18.23 and 17.6 times more rules respectively when compared to CWAC method.

![No. of rules used in the classifier for Mushroom dataset](image)

**Figure 7.48 Number of Rules Used in the Classifier for Mushroom Dataset**
Figure 7.48 shows the number of rules used in the classifier for Mushroom dataset. Both CAC and L3 methods used 30 rules in the classifier. GNP - RAC, GNP - IG AC, GARC and CWAC methods generated 9.47, 1.3, 1.26 and 1.23 times more rules respectively when compared to CAC method.

![Total Computation Time for Mushroom dataset](chart)

**Figure 7.49 Total Computation Time for Mushroom Dataset**

Figure 7.49 shows total computation time for Mushroom dataset. CAC method has the less total computation time of 32.44 seconds. In existing methods, GARC has the less computation time but it took 2.72 times more computation time as CAC. In lazy learning associative classification CHiSC has less computation time but it took about 36.9 times more computation time as CAC but lazy learning algorithm provides highest classification accuracy. Mushroom dataset consists of 23 attributes and 8124 transactions that lead to higher computation time for lazy methods but to classify a single instance CHiSC took only 0.06 seconds.
Figure 7.50 Average accuracy Comparison

Figure 7.50 depicts the comparison of accuracy for all the twelve datasets used in this research. Closed associative classification (CAC) has the classification accuracy of 84.33%. This is 0.3% improved accuracy over the existing method, L3 algorithm.

In Genetic network programming based associative classification, GNP-IG-Chi square with Mutation - I has the classification accuracy of 83.58%. This is 1.89% improved accuracy over the existing method, GNP – Random – Chi square with Mutation - I but it was lesser of 0.75% when compared to CAC method.

In weighted associative classification, Compact weighted associative classification has the classification accuracy of 82.91%. This is 0.85% improved classification accuracy over the existing method, GARC, but it was 1.42 % lesser classification accuracy when compared to CAC method.

In lazy learning methods, CHiSC has the classification accuracy of 82.08. This is 3.39% improved classification accuracy over the existing method, HiSP, but it was 2.25% lesser classification accuracy when compared to CAC.
7.3 SOLVING CLASS IMBALANCE PROBLEM

The accuracy measure is used to evaluate the performance of classifier, but it treats every class equally important. So other measures like sensitivity, specificity, Precision and recall are also used in this research to analyze the performance of the proposed associative classifiers.

7.3.1 Sensitivity and specificity

Sensitivity (True Positive Rate - TPR) and specificity (True Negative Rate- TNR) are statistical measures to evaluate the performance of a binary classification. They are also known in statistics as classification functions. High sensitivity and specificity by the classifier indicates that rare and majority classes are appropriately predicted (i.e., positive class as positive and negative class as negative).

<table>
<thead>
<tr>
<th>Dataset</th>
<th>CBA</th>
<th>GNP RAC</th>
<th>GNP – IG AC</th>
<th>L3</th>
<th>CAC</th>
<th>GARC</th>
<th>CWAC</th>
<th>HiSP</th>
<th>CHiSC</th>
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<tbody>
<tr>
<td>Breast Cancer</td>
<td>0.33</td>
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</table>

Table 7.1 Sensitivity (True Positive Rate – TPR)
Table 7.2 Specificity (True Negative Rate-TNR)

<table>
<thead>
<tr>
<th>Dataset</th>
<th>CBA</th>
<th>GNP RAC</th>
<th>GNP – 1G AC</th>
<th>L3</th>
<th>CAC</th>
<th>GARC</th>
<th>CWAC</th>
<th>HiSP</th>
<th>CHiSC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Breast Cancer</td>
<td>0.89</td>
<td>0.84</td>
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<td>0.90</td>
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<td>0.95</td>
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<tr>
<td>Breast –w</td>
<td>0.95</td>
<td>0.95</td>
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<tr>
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<td>Ionosphere</td>
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</table>

Table 7.1 shows the sensitivity and Table 7.2 shows the specificity for six datasets. For Breast cancer and Breast-w, Closed Associative Classification holds high TPR and TNR. For Credit-a, Ionosphere and mushroom datasets CHiSC holds high TPR and TNR. For diabetes dataset CWAC has high TPR and TNR rate. The eager associative classifiers construct the model before the new predictions. So the TPR and TNR rates are decreased.

### 7.3.2 Precision and recall

Precision and recall measures are useful when the dataset consists of multiple classes. So Balance Scale, Car, Ecoli, Flare and Glass dataset are taken to compute precision and recall.
Table 7.3 Precision

<table>
<thead>
<tr>
<th>Dataset</th>
<th>CBA</th>
<th>GNP RAC</th>
<th>GNP – IG AC</th>
<th>L3</th>
<th>CAC</th>
<th>GARC</th>
<th>CWAC</th>
<th>HiSP</th>
<th>CHiSC</th>
</tr>
</thead>
<tbody>
<tr>
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<td>0.64</td>
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<td>0.68</td>
<td>0.72</td>
<td>0.84</td>
<td>0.64</td>
<td>0.88</td>
<td>0.64</td>
<td>0.72</td>
</tr>
<tr>
<td>Car</td>
<td>0.43</td>
<td>0.52</td>
<td>0.55</td>
<td>0.45</td>
<td>0.69</td>
<td>0.56</td>
<td>0.59</td>
<td>0.55</td>
<td>0.55</td>
</tr>
<tr>
<td>Ecoli</td>
<td>0.67</td>
<td>0.73</td>
<td>0.73</td>
<td>0.80</td>
<td>0.80</td>
<td>0.73</td>
<td>0.73</td>
<td>0.73</td>
<td>0.80</td>
</tr>
<tr>
<td>Flare</td>
<td>0.63</td>
<td>0.68</td>
<td>0.64</td>
<td>0.75</td>
<td>0.75</td>
<td>0.71</td>
<td>0.71</td>
<td>0.66</td>
<td>0.73</td>
</tr>
<tr>
<td>Glass</td>
<td>0.50</td>
<td>0.67</td>
<td>0.67</td>
<td>0.83</td>
<td>0.83</td>
<td>0.58</td>
<td>0.83</td>
<td>0.67</td>
<td>0.75</td>
</tr>
</tbody>
</table>

Table 7.4 Recall

<table>
<thead>
<tr>
<th>Dataset</th>
<th>CBA</th>
<th>GNP RAC</th>
<th>GNP – IG AC</th>
<th>L3</th>
<th>CAC</th>
<th>GARC</th>
<th>CWAC</th>
<th>HiSP</th>
<th>CHiSC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Balance Scale</td>
<td>0.67</td>
<td>0.68</td>
<td>0.74</td>
<td>0.69</td>
<td>0.91</td>
<td>0.94</td>
<td>0.68</td>
<td>0.64</td>
<td>0.62</td>
</tr>
<tr>
<td>Car</td>
<td>0.43</td>
<td>0.52</td>
<td>0.56</td>
<td>0.85</td>
<td>0.59</td>
<td>0.50</td>
<td>0.68</td>
<td>0.48</td>
<td>0.52</td>
</tr>
<tr>
<td>Ecoli</td>
<td>0.67</td>
<td>0.69</td>
<td>0.73</td>
<td>0.63</td>
<td>0.86</td>
<td>0.73</td>
<td>0.79</td>
<td>0.61</td>
<td>0.75</td>
</tr>
<tr>
<td>Flare</td>
<td>0.88</td>
<td>0.93</td>
<td>0.92</td>
<td>0.86</td>
<td>0.88</td>
<td>0.95</td>
<td>0.83</td>
<td>0.93</td>
<td>0.84</td>
</tr>
<tr>
<td>Glass</td>
<td>0.67</td>
<td>0.80</td>
<td>0.89</td>
<td>0.71</td>
<td>0.83</td>
<td>0.88</td>
<td>0.77</td>
<td>0.73</td>
<td>0.75</td>
</tr>
</tbody>
</table>
Figure 7.51 F1 Measure for Existing System

Figure 7.52 F1 Measure for Proposed System
High precision implies that most of the predicted classes are correct. But high precision at low recall levels indicate that the classifier might not have predicted the rare class correctly. Table 7.3 and Table 7.4 depict the precision and recall of the existing and proposed associative classifiers for multiclass datasets.

The proposed systems have high precision and recall compared to CBA and the existing algorithms. A drop in the metrics was observed for the lazy learning associative classification, HiSC though it was better than the existing lazy learning algorithms.

Figure 7.51 shows the F1 – measure for the existing methods. Performance of the existing L3 algorithms was high for most of the datasets. Figure 7.52 shows the F1-measure for the proposed system. Here the Closed Associative Classifier provides higher performance when compared to the existing and other proposed methods because of the closed itemset. The closed itemset consists of all the information about its subset also. So the Closed Associative Classifier performance is always high.

7.4 ACCURACY PERFORMANCE VALIDATION

To validate the statistical significance of the proposed associative classification algorithms, cross validated paired t – test (Dietterich, 1998) was performed. The test has been performed at level \( p = 0.05 \) for all the datasets. All the proposed algorithms are compared against CBA and the existing associative classifiers using 12 datasets. Table 7.5 reports the significant evaluation results.
Table 7.5 Paired t-test

<table>
<thead>
<tr>
<th>Method</th>
<th>CBA</th>
<th>GNP AC-RAC</th>
<th>GARC</th>
<th>L3</th>
<th>HiSP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed Methods</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(X)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GNP Lift MII</td>
<td>6/3</td>
<td>4/1</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>CAC</td>
<td>8/1</td>
<td>-</td>
<td>5/3</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>CWAC</td>
<td>9/0</td>
<td>5/3</td>
<td>-</td>
<td>-</td>
<td>6/4</td>
</tr>
<tr>
<td>CHiSC</td>
<td>9/2</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

X/Y indicates that Proposed method is significantly better X times (Worst Y times) than the Existing method.

For example, when comparing GNP Associative Classification (Lift Measure with Mutation II) with CBA, the GNP AC has improved the classification accuracy for 6 datasets (worst for 3 datasets). When compared with GNP RAC, the proposed system performs well for 4 datasets and the existing method performs well for only one dataset. So Table 7.5 proves that the proposed system is statistically significant.

7.5 CONCLUSION

This thesis has surveyed different associative classification approaches and proposed new innovative techniques in both eager and lazy learning associative classification. The main aim is to generate minimum number of class association rules thereby constructing optimal associative classifier without compromising the classification accuracy. The experiments are done on 12 UCI benchmark datasets. The results of the proposed associative classification methods are discussed below.
GNP-IG-AC method selects information gain attributes and constructs genetic network tree. This method applies chi-square and Lift measures for rule evaluation. GNP – IG-AC – Mutation - I with chi-square fitness evaluation measure has 1.89% improved classification accuracy when compared with existing GNP-RAC-Mutation - I. GNP-IG-AC-Mutation - II with Lift has 1.73% improved classification accuracy when compared with GNP – RAC- Mutation – II. These techniques results with minimum number of high quality rules. It was observed that the GNP constructed using best attribute consumed lesser computation time and converged quickly when compared to random attribute selection. However the computation time is still high and needs further investigations to reduce time without compromising accuracy.

Closed associative classification extends closed itemset mining for extracting class association rules. This work proposes two classifier construction methods namely, GRS and Eager closed classifier. Classification accuracy using GRS classifier has 0.83% improved when compared with CBA. However a drop in classification accuracy is observed when compared with the existing L3 method. It is due to presence of conflict rules in the classifier. This motivates to propose eager closed associative classifier which removes conflict rules and outperforms L3.

Current associative classification methods ignore some class association rules based on their frequency in training dataset, which user may benefit from. CWAC overcomes this by prioritizing the rule according to their importance by using weights. This research uses HITS model for calculating weight, which eliminates the need for pre-assigning the weights manually. CWAC (with minimum confidence > 70%) holds the highest classification accuracy of 84.62% and outperformed all existing methods investigated.
Lazy learning associative classification eliminates the need of construing the generalized classifier. This research work discusses about three lazy learning associative classification methods namely, HiSC, CHiSP, and CHiSC. HiSC is a variation of HiSP-GC which calculates subset confidence for testing instance and assigns class based on that. This method has 0.63% improved classification accuracy over HiSP - GC but has high computation time. To reduce the computational time CHiSP and CHiSC are proposed. CHiSP and CHiSC choose one non class informative attribute and generate subsets based on that. CHiSP uses subset probability to assign class whereas CHiSC uses subset confidence to assign class. CHiSP and CHiSC have 1.21% and 1.55% improved classification when compared to HiSP-GC and they took 0.115 and 0.0097 seconds to classify an instance. So both methods outperformed existing HiSP-GC method in classification accuracy and computation time.

The various experimental results reveal that the rulesets are optimal and the proposed methods outperformed existing associative classification methods.