**STATLOG (VEHICLE SILHOUETTES)**

**Abstract**: 3D objects within a 2D image by application of an ensemble of shape feature extractors to the 2D silhouettes of the objects

J48 CLASSIFIER:

=== Summary ===

Correctly Classified Instances 637 75.2955 %

Incorrectly Classified Instances 209 24.7045 %

Kappa statistic 0.6705

Mean absolute error 0.1278

Root mean squared error 0.3298

Relative absolute error 34.0673 %

Root relative squared error 76.0944 %

Total Number of Instances 846

=== Detailed Accuracy By Class ===

TP Rate FP Rate Precision Recall F-Measure MCC ROC Area PRC Area Class

0.627 0.132 0.613 0.627 0.620 0.491 0.779 0.549 opel

0.558 0.145 0.571 0.558 0.564 0.416 0.762 0.511 saab

0.945 0.014 0.958 0.945 0.952 0.935 0.977 0.955 bus

0.889 0.039 0.876 0.889 0.883 0.846 0.942 0.841 van

Weighted Avg. 0.753 0.083 0.753 0.753 0.753 0.670 0.864 0.713

=== Confusion Matrix ===

a b c d <-- classified as

133 70 2 7 | a = opel

79 121 4 13 | b = saab

2 5 206 5 | c = bus

3 16 3 177 | d = van

NAÏVE BAYES CLASSIFIER:

=== Summary ===

Correctly Classified Instances 381 45.0355 %

Incorrectly Classified Instances 465 54.9645 %

Kappa statistic 0.2729

Mean absolute error 0.286

Root mean squared error 0.4656

Relative absolute error 76.2123 %

Root relative squared error 107.4132 %

Total Number of Instances 846

=== Detailed Accuracy By Class ===

TP Rate FP Rate Precision Recall F-Measure MCC ROC Area PRC Area Class

0.420 0.172 0.449 0.420 0.434 0.254 0.696 0.421 opel

0.401 0.121 0.534 0.401 0.458 0.310 0.710 0.492 saab

0.133 0.024 0.659 0.133 0.221 0.215 0.842 0.586 bus

0.884 0.410 0.399 0.884 0.550 0.403 0.824 0.534 van

Weighted Avg. 0.450 0.177 0.513 0.450 0.413 0.293 0.767 0.508

=== Confusion Matrix ===

a b c d <-- classified as

89 58 2 63 | a = opel

61 87 2 67 | b = saab

44 10 29 135 | c = bus

4 8 11 176 | d = van

IBK CLASSIFIER:

=== Summary ===

Correctly Classified Instances 590 69.74 %

Incorrectly Classified Instances 256 30.26 %

Kappa statistic 0.5964

Mean absolute error 0.1524

Root mean squared error 0.3881

Relative absolute error 40.5972 %

Root relative squared error 89.5326 %

Total Number of Instances 846

=== Detailed Accuracy By Class ===

TP Rate FP Rate Precision Recall F-Measure MCC ROC Area PRC Area Class

0.462 0.151 0.505 0.462 0.483 0.320 0.655 0.368 opel

0.498 0.173 0.498 0.498 0.498 0.324 0.662 0.377 saab

0.945 0.033 0.907 0.945 0.926 0.900 0.956 0.872 bus

0.894 0.046 0.856 0.894 0.875 0.835 0.924 0.790 van

Weighted Avg. 0.697 0.102 0.689 0.697 0.693 0.592 0.798 0.599

=== Confusion Matrix ===

a b c d <-- classified as

98 97 6 11 | a = opel

87 108 9 13 | b = saab

3 3 206 6 | c = bus

6 9 6 178 | d = van

LWL CLASSIFIER:

=== Summary ===

Correctly Classified Instances 386 45.6265 %

Incorrectly Classified Instances 460 54.3735 %

Kappa statistic 0.2809

Mean absolute error 0.326

Root mean squared error 0.3992

Relative absolute error 86.864 %

Root relative squared error 92.0991 %

Total Number of Instances 846

=== Detailed Accuracy By Class ===

TP Rate FP Rate Precision Recall F-Measure MCC ROC Area PRC Area Class

0.307 0.115 0.471 0.307 0.371 0.225 0.738 0.415 opel

0.438 0.194 0.438 0.438 0.438 0.244 0.744 0.465 saab

0.124 0.000 1.000 0.124 0.220 0.308 0.778 0.682 bus

1.000 0.410 0.429 1.000 0.600 0.503 0.910 0.668 van

Weighted Avg. 0.456 0.175 0.589 0.456 0.403 0.317 0.790 0.556

=== Confusion Matrix ===

a b c d <-- classified as

65 82 0 65 | a = opel

53 95 0 69 | b = saab

20 40 27 131 | c = bus

0 0 0 199 | d = van

KSTAR CLASSIFIER:

=== Summary ===

Correctly Classified Instances 597 70.5674 %

Incorrectly Classified Instances 249 29.4326 %

Kappa statistic 0.6075

Mean absolute error 0.1526

Root mean squared error 0.3575

Relative absolute error 40.6749 %

Root relative squared error 82.4776 %

Total Number of Instances 846

=== Detailed Accuracy By Class ===

TP Rate FP Rate Precision Recall F-Measure MCC ROC Area PRC Area Class

0.410 0.158 0.465 0.410 0.436 0.264 0.780 0.445 opel

0.484 0.180 0.482 0.484 0.483 0.304 0.785 0.442 saab

0.991 0.016 0.956 0.991 0.973 0.964 0.999 0.998 bus

0.950 0.040 0.879 0.950 0.913 0.886 0.992 0.974 van

Weighted Avg. 0.706 0.099 0.693 0.706 0.699 0.601 0.888 0.711

=== Confusion Matrix ===

a b c d <-- classified as

87 108 6 11 | a = opel

95 105 4 13 | b = saab

0 0 216 2 | c = bus

5 5 0 189 | d = van

**ANALYSIS PART:**

There are 4 Four "Corgie" model vehicles : a double decker bus, Cheverolet van, Saab 9000(car)and an Opel Manta 400(car). The particular combination of vehicles was chosen with the expectation that the bus, van and either one of the cars would be readily distinguishable, but it would be more difficult to distinguish between the cars.

So among this 5 classifiers, that classifier will be the suitable who will give maximum correctly classified instances and also give maximum correctly distinguish between two cars. For this Purpose, consider one of the cars as a positive interest and the other vehicles as a negative.

**For J48:**

Correctly Classified Instances 637 75.2955 %

**Confusion Matrix:**

a b c d <-- classified as

133 70 2 7 | a = opel

79 121 4 13 | b = saab

2 5 206 5 | c = bus

3 16 3 177 | d = van

Consder a(opel) as a positive interest and others(saab,bus,van) as a negative.

**New Confusion Matrix:**

a b<-- classified as

133 79 | a = opel | TPR=(133)/(133+79)=0.63

84 550| b = others | FPR=(84)/(84+550)=0.13

Consder a(saab) as a positive interest and others(opel,bus,van) as a negative.

b a c d <-- classified as b a c d <-- classified as

70 133 2 7 | a = opel 121 79 4 13 | b = saab

121 79 4 13 | b = saab ------------🡪 70 133 2 7 | a = opel

5 2 206 5 | c = bus 5 2 206 5 | c = bus

16 3 3 177 | d = van 16 3 3 177 | d = van

**New Confusion Matrix:**

a b<-- classified as

121 96 | a = saab | TPR=121/(121+96)=0.56

91 538| b = others | FPR=91/(91+538)=0.15

**NaiveBayes:**

Correctly Classified Instances 381 45.0355 %

**Confusion Matrix:**

a b c d <-- classified as

89 58 2 63 | a = opel

61 87 2 67 | b = saab

44 10 29 135 | c = bus

4 8 11 176 | d = van

Consder a(opel) as a positive interest and others(saab,bus,van) as a negative.

**New Confusion Matrix 1:**

a b<-- classified as

89 123 | a = opel | TPR=89/(123+89)=0.42

109 525| b = others |FPR=109/(109+525)=0.17

Consder a(saab) as a positive interest and others(opel,bus,van) as a negative.

b a c d <-- classified as b a c d <-- classified as

58 89 2 63 | a = opel 87 61 2 67 | b = saab

87 61 2 67 | b = saab ------------🡪 58 89 2 63 | a = opel

10 44 29 135 | c = bus 10 44 29 135 | c = bus

8 4 11 176 | d = van 8 4 11 176 | d = van

**New Confusion Matrix 2:**

a b<-- classified as

87 130 | a = saab |TPR=87/(87+130)=0.4

76 553| b = others |FPR=76/(76+553)=0.12

**IBK:**

Correctly Classified Instances 590 69.74 %

Confusion Matrix:

a b c d <-- classified as

98 97 6 11 | a = opel

87 108 9 13 | b = saab

3 3 206 6 | c = bus

6 9 6 178 | d = van

Consder a(opel) as a positive interest and others(saab,bus,van) as a negative.

**New Confusion Matrix 1:**

a b<-- classified as

98 114 | a = opel |TPR=98/(98+114)=0.46

96 538| b = others |FPR=96/(96+538)=0.15

Consder a(saab) as a positive interest and others(opel,bus,van) as a negative.

b a c d <-- classified as b a c d <-- classified as

97 98 6 11 | a = opel 108 87 9 13 | b = saab

108 87 9 13 | b = saab ------------🡪 97 98 6 11 | a = opel

3 3 206 6 | c = bus 3 3 206 6 | c = bus

9 6 6 178 | d = van 9 6 6 178 | d = van

**New Confusion Matrix 2:**

a b<-- classified as

108 109 | a = saab |TPR=108/(108+109)=0.51

109 520| b = others |FPR=109/(109+520)=0.17

**LWL:**

Correctly Classified Instances 386 45.6265 %

Confusion Matrix:

a b c d <-- classified as

65 82 0 65 | a = opel

53 95 0 69 | b = saab

20 40 27 131 | c = bus

0 0 0 199 | d = van

Consder a(opel) as a positive interest and others(saab,bus,van) as a negative.

**New Confusion Matrix 1:**

a b<-- classified as

65 147 | a = opel | TPR=65/(65+147)=0.31

73 561| b = others |FPR=73/(73+561)=0.12

Consder a(saab) as a positive interest and others(opel,bus,van) as a negative.

b a c d <-- classified as b a c d <-- classified as

82 65 0 65 | a = opel 95 53 0 69 | b = saab

95 53 0 69 | b = saab ------------🡪 82 65 0 65 | a = opel

40 20 27 131 | c = bus 40 20 27 131 | c = bus

0 0 0 199 | d = van 0 0 0 199 | d = van

**New Confusion Matrix 2:**

a b<-- classified as

95 122 | a = saab | TPR=95/(95+122)=0.44

122 507| b = others | FPR=122/(122+507)=0.21

**KSTAR:**

Correctly Classified Instances 597 70.5674 %

**Confusion Matrix:**

a b c d <-- classified as

87 108 6 11 | a = opel

95 105 4 13 | b = saab

0 0 216 2 | c = bus

5 5 0 189 | d = van

Consder a(opel) as a positive interest and others(saab,bus,van) as a negative.

**New Confusion Matrix 1:**

a b<-- classified as

87 125 | a = opel | TPR=87/(87+125)=0.41

100 534| b = others | FPR=100/(100+534)=0.16

Consder a(saab) as a positive interest and others(opel,bus,van) as a negative.

b a c d <-- classified as b a c d <-- classified as

108 87 6 11 | a = opel 105 95 4 13 | b = saab

105 95 4 13 | b = saab ------------🡪 108 87 6 11 | a = opel

0 0 216 2 | c = bus 0 0 216 2 | c = bus

5 5 0 189 | d = van 5 5 0 189 | d = van

**New Confusion Matrix 2:**

a b<-- classified as

105 112 | a = saab | TPR=105/(105+112)=0.48

113 516| b = others | FPR=113/(113+516)=0.18

After analysis all the classifier we can choose a suitable classifier according to maximum correct classified instances and which classsifer can most correctly distinguish between car. For find the classifier give the most correctly distinguish between car we can consider opel or saab as a positive interest and others as a negative interest.

For getting the final result we have consider opel as a positive interest and according this draw a ROC graph.

**SUMMARY:**

After implementing 5 classifiers, we have seen that the J48 classifier can Correctly Classify 637 Instances with 75.2955 % accuracy. Naive-Bayes classifier can Correctly Classify 381 instances with 45.0355 % accuracy. IBK classifier can Correctly Classify 590 instances with 69.74 % accuracy. LWL classifier can Correctly Classify 386 instances with 45.6265 % accuracy. Kstar classifier can Correctly Classify 597 instances with 70.5674 %accuracy.

So, In that case, the J48 classifier gives the maximum number of correctly classified instances. But we have to check another requirement that which classifier mostly distinguishes between two cars correctly. The target is to identify the car correctly. Identifying the bus, van, saab as a opel is not a problem but identifying opel as a bus ,van or saab is a problem.

In the J48 classifier, distance c1 is the closest to the best possible classifier(1) among other classifiers’ distances. And can distinguish 133 opel(car) correctly among 212 opel .NaiveBayes can distinguish 89 opel Correctly among 212 opel.It is less better than J48 and distance is far from best possible classifier.IBK can distinguish 98 opel Correctly among 212 opel.It is also less better than J48 and distance is far from best possible classifier. LWL can distinguish 65 opel Correctly among 217 opel.It is also less better than J48 and distance is far from best possible classifier. Kstar can distinguish 87 opel Correctly among 217 opel. It is less better than J48 and distance is far from the best possible classifier.

In my point of view J48 classifier is suitable for this case. Because the J48 classifier distinguishes most correctly classified instances and also can identify most instances between cars correctly among other classifiers.