$C' = c^{\tau} + C$;
record the accuracy of c^i as $ACC_i^{(+)}$
end for;
record the accuracy of C on D_{ad} as ACC_c;
p = type($argmax_i\ ACC_i^{(-)}$)
q = $argmax_i\ ACC_i^{(+)}$
if $ACC_p > ACC_c$ and ACCp > ACCq:
$t_p = t_p - 1$, m = m − 1;
else if $ACC_q > ACC_p$ and $ACC_p > ACC_q$
$t^q = t^p + 1$, m = m + 1;
else: remain the current V ;

end if;

All variants and the current ensemble are tested on the adaptation set for accuracy. If one variant with reduced size achieves the best accuracy, then the number of classifiers of its corresponding type is decreased by one. The numbers of instances of other types remains the same, thereby leading to a reduction of one in the size of the ensemble. If one variant with increased size achieves the best accuracy, then the number of classifiers of its corresponding type is increased by one. The numbers of instances of other types remains the same, thereby leading to an addition of one in the size of the ensemble. If the current ensemble achieves the highest accuracy, the size and internal ratio of classifier types remain unchanged.

3. Findings

In this paper we have reviewed four ensemble methodology used for classification. In first methodology we have seen ENS outperforming other ensemble by creating extended feature set which improves classification accuracy and also generates smaller (simple) base learner. Whereas in second methodology resampling based ensemble outperforms other algorithm in statistical test. Third methodology for classification is proposed in heterogeneous Ensembling method the basic advantage of this method logy is use of algorithmically different type of classifier .the TLS classifier has shown its efficiency and accuracy for microarray data classification, which has scope in biomedical sciences.

Classifier Types	C45		NB		KNN		Improvement
Data Sets	mean	std	mean	std	mean	std	
letter	0.71	0.05	0.11	0.04	0.19	0.04	1.068
mfeat-pixel	0.37	0.07	0.2	0.05	0.43	0.07	1.056
isolet	0.58	0.07	0.18	0.04	0.24	0.05	1.05
mfeat-karhunen	0.43	0.08	0.2	0.06	0.37	0.07	1.05
mfeat-zernike	0.31	0.1	0.23	0.08	0.46	0.09	1.047
mfeat-fourier	0.53	0.09	0.25	0.05	0.22	0.06	1.041
segment	0.54	0.09	0.12	0.08	0.34	0.1	1.032
spambase	0.57	0.12	0.15	0.06	0.28	0.1	1.031
mfeat-factors	0.53	0.08	0.16	0.09	0.31	0.09	1.024
pendigits	0.37	0.1	0.06	0.05	0.57	0.09	1.023
optdigits	0.32	0.09	0.15	0.05	0.53	0.08	1.02
splice	0.44	0.09	0.41	0.1	0.15	0.07	1.019
landsat	0.49	0.1	0.08	0.05	0.44	0.09	1.019
page	0.61	0.12	0.2	0.11	0.18	0.11	1.012
waveform(2)	0.34	0.09	0.34	0.07	0.32	0.09	1.009
mus	0.66	0.15	0.15	0.1	0.2	0.16	1.004
madelon	0.34	0.17	0.31	0.13	0.36	0.19	0.996
magic	0.4	0.11	0.21	0.08	0.39	0.11	0.993
average percentage — rank correlation	0.474	-0.75	0.195	-0.65	0.332	-0.75	

Figure 5: Comparison of AHE vs. Other classifiers [15]

4. Conclusion

From above survey we can conclude that ensemble classifier is efficient and classification is more accurate. Also, the algorithms which include the modified bagging and boosting for decision tree generation are more reliable and accurate than the conventional algorithms.

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