TABLE XII
EXPERIMENTAL RESULTS ON T-TEST BETWEEN THREE DIFFERENT KERNELS

Mean Difference											
MAE				MRE				RMSE			
	Linear	Polynomial	RBF		Linear	Polynomial	RBF		Linear	Polynomial	RBF
Linear	0.000	0.007	-0.021	**Linear**	0.000	0.005	-0.084	**Linear**	0.000	0.005	-0.018
Polynomial	-0.007	0.000	-0.028	**Polynomial**	-0.005	0.000	-0.090	**Polynomial**	-0.005	0.000	-0.023
RBF	0.021	0.028	0.000	**RBF**	0.084	0.090	0.000	**RBF**	0.018	0.023	0.000
p-value											
MAE				MRE				RMSE			
	Linear	Polynomial	RBF		Linear	Polynomial	RBF		Linear	Polynomial	RBF
Linear	NaN	0.13	0.001	**Linear**	NaN	0.467	0.000	**Linear**	NaN	0.121	0.007
Polynomial	0.13	NaN	0.000	**Polynomial**	0.467	NaN	0.000	**Polynomial**	0.121	NaN	0.005
RBF	0.001	0.000	NaN	**RBF**	0.000	0.000	NaN	**RBF**	0.007	0.005	NaN

Squared Error (RMSE). Hence for each kernel a total three set (one for each performance measure) are used, each with 90 data points (six subsets of metrics multiplied by 15 QoS). The experimental results of t-test analysis for different performance parameter (MAE, MMRE and RMSE) and three different ELM kernels are summarized in Table XII. Table XII contains two parts. The first part of the table XII shows the mean difference value and second part shows the p-value between different pairs. Table XII reveals that there is no significant difference between the kernel function, due to the fact that p-value is greater than 0.05. However, by closely examining the value of mean difference, polynomial kernel yields better result compared to other kernels function i.e., linear and RBF kernel functions.

X. CONCLUSION

We develop a predictive model to estimate QoS parameters of web services using source code (implementing the services) metrics. We experiment with six different sets of metrics as input to develop a prediction model. The performance of these sets of metrics are evaluated using Extreme Learning Machines (ELM) with various kernel functions such as linear, polynomial and RBF kernel function. From the correlation analysis between metrics, we observe that there exists a high correlation between Object-Oriented metrics and WSDL metrics. From t-test analysis, we infer that in most of the cases, there is the difference between the various sets of metrics in terms of the performance of the estimator is not substantial but moderate. We observe that the predictive model developed using Harry M. Sneed (HMS) metrics yields better result compared to other sets of metrics such as all metrics and Baski and Misra metrics. From t-test analysis, we can also interpret that difference between the three kernel functions in-terms of their influence on the predictive accuracy is moderate. We conclude that none of the feature selection technique dominate the other and one feature selection method is better than the other for some QoS parameters and vice-versa. By assessing the value of mean difference, we infer that the polynomial kernel for ELM yields better result compared to other kernels function i.e., linear and RBF kernel functions. From performance results, it is observed that the performance of the predictive model or estimator varies with the different sets of software metrics, feature selection technique and the kernel functions. Finally, we conclude that it is possible to estimate the QoS parameters using ELM and source code metrics.

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