Quality Assessment of Web Services using multivariate adaptive regression splines

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***Abstract*—The need to chose a suitable web service in the present scenario, due to the high growth in number of web services that provide similar types of functionalities is a critical task. To select a suitable web service, quality of service (QoS) parameters are efficient to use. In this paper, nine parameters of QoS have been considered as input for design a model using multivariate adaptive regression splines (MARS) to select suitable web service. The performance parameters of MARS model are evaluated and compared with those obtained using models such as: Multivariate Linear Regression, Multivariate Polynomial Regression, Naives Bayes Classifier, Artificial Neural Network. It is observed that the proposed model designed using MARS technique achieved better results as compared to the other three techniques. This paper also focuses on the effectiveness of feature selection techniques to find a small subset of QoS parameters. These may be able to classify the web services with higher accuracy and also reduced the value of misclassification errors.**

***Keywords*—ANN, MARS, MLR, MPR, Naives Bayes, Web Service, WSRF.**

I. Introduction

Service oriented computing paradigm has an important aspect in the present-day era of software development. Service oriented computing paradigm assembles loosely coupled pieces of software called services, which enable the construction of distributed system. With the increasing use of web services, a good number of Web-services are available that provide similar types of functionalities. One of the major objectives of service consumers is to select a suitable web service. It is observed that selection of suitable web services is assessed by the use of Quality of Service (QoS) parameters such as Availability (AV), Best Practices (BP), Compliance (CP), Documentation (DOC), Latency (LT), Response Time (RT), Reliability (REL), Throughput (TP), and Success ability (SA) etc..

In order to select suitable a web service, several traditional techniques are available in literature as proposed by different authors. In this study, multivariate adaptive regression splines (MARS) technique has been considered for designing a model to select a suitable web service by considering various QoS parameters as input. Different performance parameters of MARS model are evaluated and compared with those obtained using other models such as: Multivariate Linear Regression (MLR), Multivariate Polynomial Regression (MPR), Naive Bayes Classifier, Artificial Neural Network (ANN). It is observed that the proposed model designed using MARS technique achieved better results as compared to the other three techniques. This paper also focuses on the effectiveness of feature selection techniques to find a small subset of QoS parameters in order to improve accuracy and also reduced the value of misclassification errors.

Feature selection is a process of finding a subset of QoS parameters which are able to predict maintainability with higher accuracy and also reduce the value of misclassification errors. Feature selection techniques can be broadly classified into two subclasses i.e., feature ranking and feature subset selection. In feature ranking techniques, a number of decisive factors have been considered to rank each individual feature and then few features are selected, suitable for a given project. While in feature subset selection, subset of features are searched which have collectively a better predictive capability. In this study, four different types of feature ranking and feature subset selection techniques have been considered to find a small subset of QoS parameters which may help to classify the web services with higher accuracy and reduce the value of misclassification errors.

The remainder of the paper is organized as follows: Section II highlights the related work in the field of selection of web service. Section III highlights on research background related to this study. Section IV discuses on the different feature selection technique considered to find a small subset of QoS parameters. Section V illustrates the techniques used to design a model. Section VI discuses on the results and its analysis. Section VII provides comparison on the performance of the designed models. Section VIII points out threats to validity and Section IX concludes the paper with scope for future work.

II. Related work

This section presents a review of literature on the use of different types of QoS parameters and their application for selecting the suitable web service.

Eyhab Al-Masri et al. have considered various QoS parameters to design web service relevancy ranking function (WSRF) [1]. This function is used to find the best suitable web service during the discovery process of Web services. They analyzed different non-functional properties of Web services which significantly improve the probability of web service having relevant output results. Their proposed work shows the usefulness and effectiveness of various QoS parameter for selection of Web services during the discovery process.

Mohanty et al. have applied back propagation neural network (BPNN), probabilistic neural network (PNN), group method of data handling (GMDH), TreeNet, classification and regression trees (CART), support vector machine (SVM) and ID3 decision tree (J48) techniques to design a model to predict the quality of a web service by considering QoS attributes as input [8]. They observed that performance of designed model is comparatively better when WSRF along with QoS attributes are considered as input. They also observed that, performance of all models falls down miserably when the design model does not consider WSRF as one of the inputs.

LI Yuan-jie et al. have three different types of classification techniques i.e., Naive Bayes, SVM, REPTree to design a model for classifying the WSDL data [12]. In their proposed work, they ahve considered automatic web service semantic annotation and used furthermore, ensemble learning is applied. Their proposed work get 87.39% accuracy on 19 different categories of 951 WSDL files.

Ramakanta Mohanty et al. considered Naive Bayes, Markov blanket and Tabu search techniques for designing a model to rank the web services [7]. They used dataset consists of nine different quality parameters of 364 web services. They concluded that Naive Bayes classifier achieves better result as compared to other two techniques.

From literature, it is understood that the ranking of web service can be predicted using QoS parameter. In this study, nine different types of QoS parameter have been considered to design a model using MARS technique for classifying the web services.

III. RESEARCH BACKGROUND

The following subsections highlight on the data set used for classification of the web services.

A. Classification of web services

Numerous service providers provide usually web services of similar category in different forms and variations i.e., the same service with different feature sets and pricing policies. For example, Amazon Web Service (AWS) provided by Amazon.com allows developers to partially access its web service. However, Amazon.com may provide different varieties of AWS service based on their QoS parameters for example AWS provides services with throughput of 1,000 invocations/second (i.e. type Platinum or class 4) while AWS Basic also provides services with a maximum throughput of 200 invocations/second (i.e. type Bronze or class 1). Table I shows the sample of web service class for AWS Basic.

TABLE I: Web service classes for AWS

AWS service offering	Description
Enterprise	Platinum (class4)
Professional	Gold (class3)
Ultra	Silver (class2)
Basic	Bronze (class1)

Web services are categorized based of the QoS parameter or properties i.e, Platinum provides higher levels of quality while service under the Bronze class offer the same functionality but at a lower quality. In this paper, MARS has been considered to design a model for classifying the web service classes.

B. Quality of service (QoS) parameter

Selection of suitable web services is assessed by the use of Quality of Service (QoS) parameters. In this paper, nine different types of QoS parameters have been considered for designing a model to classifying the web services. The QoS parameters selected in this study are tabulated in Table II.

TABLE II: QoS Parameters

Parameter Name	Description	Unit
Availability (AV)	Number of successful invocations/total invocations	%
Best Practices (BP)	The extent to which a Web service follows WS-I Basic Profile	%
Compliance (CP)	The extent to which a WSDL document follows WSDL specification	%
Documentation (DOC)	Measure of documentation (i.e. description tags) in WSDL	%
Latency (LT)	Time taken for the server to process a given request	ms
Response Time (RT)	Time taken to send a request and receive a response	ms
Reliability (REL)	Ratio of the number of error messages to total messages	%
Success ability (SA)	Number of responses / number of request messages	%
Throughput (TP)	Total Number of invocations for a given period of time	Invokes per second
WSRF	Web Service Relevancy Function: a rank for Web Service Quality	%
Service Classification	Levels representing service offering qualities (1 through 4)	Classifier

C. Effectiveness of QoS Parameters

To analyze the effectiveness of the QoS Parameters used, they are categorized into different groups as shown below:

a. **Analysis 1 (A1)**: Since web service relevancy ranking function (WSRF) is the most important parameter of web services, two different forms analysis have been considered for classifying the web services i.e., the first one taken for all QoS parameters along with WSRF and the other one is for all QoS parameters without WSRF. The relationship of all QoS parameters along with WSRF for web service class is represented as follows:

$$Web\ service\ class = f(RT, AV, TP,$$
$$SA, REL, CP, BP, LT, DOC, WSRF)$$

a. **Analysis 2 (A2)**: In this analysis, all QoS parameters are considered without considering WSRF as input to design a model for classifying the web services. Their relationship with class is represented as follows:

$$Web\ service\ class = f(RT, AV, TP,$$
$$SA, REL, CP, BP, LT, DOC)$$

b. **Analysis 3 (A3)**: In this analysis, reduced feature attributes using feature ranking techniques are considered as input to design a model for classifying the web services. Their relationship with class is represented as follows:

$$Web\ service\ class = f(Reduced\ subset\ of\ QoS$$
$$parameter\ using\ feature\ reduction\ techniques)$$

c. **Analysis 4 (A4)**: In this analysis, reduced feature attributes using feature subset selection techniques are considered as input to design a model for classifying the web services. Their relationship with class is represented as follows:

$$Web\ service\ class = f(Reduced\ subset\ of\ QoS\ parameter\ using\ feature\ subset\ selection\ techniques)$$

D. Research Questions

The motivation behind study is to design a model for classifying the web services using different QoS parameters. This study also intends to focus on identifying the best possible subset of QoS parameters for classifying the web services. The research questions may be put up as:

RQ1 Whether it is possible to design a model for classifying the web services using QoS parameter ?
This question investigates the performance of design model for classifying the web services by considering QoS parameters as input.

RQ2: Whether there exists a subset of QoS parameters that are better for classifying the web services ?
This step aims to evaluate the QoS parameters to test their relationship with web service class. In this study, different types of feature reduction techniques have been considered for finding subsets of QoS parameters which can perform in better way for classifying the web services.

RQ3: Which feature ranking techniques work the best for classifying the web services?
Feature ranking techniques performance depends on the nature of the dataset. Each technique uses different parameters to rank the features.

RQ4: Which feature subset selection technique works best for classifying the web services?
Each feature subset selection technique can be used in a different way to find subset of features which can perform in better way for classifying the web services.

RQ5: Does the feature selection techniques affect the performance of the classification techniques ?
This question investigates the variation of performance of a classification technique over other classification techniques. It may be possible that some feature selection techniques may work very well with a specific classification technique.

E. Case study

In this paper, to analyze the effectiveness of the proposed approach, publicly available Quality of Web Service (QWS) dataset are considered as case study. QWS dataset contain the quality of service (QoS) parameters of 364 different number of web services [1]. Web Service Crawler Engine (WSCE) are considered for collecting the web services. Most of the web services are taken from public sources on the Web including Universal Description, Discovery, and Integration (UDDI) registries, search engines, and service portals. Nine different types of QoS parameters mentioned in Table II are considered to measure each web service using commercial benchmark tools. Each service has been tested over a ten-minute period for three consecutive days.

IV. Feature selection techniques

The following sub-sections highlight on different feature selection techniques to find a small subset of QoS parameters out of total available QoS parameters which may help to classify web service with higher accuracy and reduce the value of misclassification errors. In a broad way, feature reduction techniques can be categorized into two groups such as:

A. Feature ranking techniques

Feature ranking techniques rank features independently without using any learning algorithm. When the feature ranking techniques are considered, ranking of features are based on score of the features. In this study, four feature ranking techniques have been considered for computing the score of feature. These feature-ranking techniques are described below:

1) Chi-Squared test: Chi-Squared test is used to test the independence between two events [10]. In chi Squared test, ranking of features are based on the value of the chi-squared statistic with respect to the class.

2) Gain Ratio Feature Evaluation Technique: In gain ratio feature evaluation technique, ranking of features are based on the value of the gain ratio with respect to the class [9].

3) Information Gain Feature Evaluation Technique: In info gain feature evaluation technique, importance of features are based on the value of the information gain with respect to the class [9].

4) Principal Component Analysis (PCA): The application of PCA is considered in order to transfer a data space of high dimension into a lower dimension of feature space having the most significant features [11]. PCA rigidly rotates the axes of the p-dimension space to new position (principle axes) such that principal axis 1 has the highest variance, axis 2 has the next highest variance and so on.

B. Feature subset selection techniques

Feature-subset selection techniques are used to find suitable subset of features which collectively have good predictive capability. Feature-subset selection techniques are based on the assumption that model has higher accuracy and reduced value of misclassification errors when combined with some other features. In this study, four feature subset selection techniques have been considered for computing the score of feature. These feature subset selection techniques may be identified as:

1) Classifier Subset Evaluation Technique: Classifier subset evaluation technique uses classifier technique to estimate the 'merit' of the possible subsets of features of the project [3]. The 'merit' considered is the minimum classification error. Commonly it uses a search technique, which finds small subset of features which assesses using the evaluation technique. In this study Naive Bayes classifier may be considered as classifier technique.

2) Consistency Subset Evaluation Technique: Consistency subset evaluation technique evaluates the worth of a subset of attributes by the level of consistency in the class values when the training instances are projected onto the subset of attributes.

3) Filtered Subset Evaluation Technique: Filtered subset evaluation technique is a method for running a random subset evaluator on dataset which are passed through an arbitrary filter [5]. The filter approach does not depend on any learning induction algorithm. The computational complexity of filter approach is simple, fast, and scalable.

4) Correlation based Feature Selection Technique: Correlation based feature selection (CFS) subset evaluation technique selects a subset of features that are highly correlated with the class. In this study, Pearson′s correlations (r: Coefficient of correlation) has been considered for finding the dependency between metrics.

V. PROPOSED WORK FOR PREDICTING WEB SERVICE SELECTION

Two most commonly used techniques, to design a classification model are multivariate linear regression, multivariate polynomial regression analysis, Naive Bayes classifier, and support vector machine. The multivariate adaptive regression splines (MARS) technique is further applied for designing a prediction model.

A. Multivariate Linear Regression (MLR) Analysis

Linear regression is the commonly used as a statistical technique [2]. Linear regression is used to study the linear (i.e., straight-line) relationship between dependent and independents variables.

The multivariate linear regression is expressed as :

$$Y = \alpha_0 + \alpha_1 X_1 + \alpha_2 X_2 + ... + \alpha_p X_p \tag{1}$$

Where X_i, y are the i_{th} independent variable and dependent variable respectively.

B. Multivariate Polynomial regression analysis (MPR)

Polynomial regression is the commonly used as a statistical technique. Polynomial models are mostly used when the analyst is aware of that curvilinear effects are present in the true response function.

For the multivariate second order Polynomial regression analysis, the Polynomial regression of two variable is based on:

$$Y = \alpha_0 + \alpha_1 X_1 + \alpha_2 X_2 + \alpha_{11} X_1^2 + \alpha_{22} X_2^2 + \alpha_{12} X_1 X_2 \tag{2}$$

C. Naive Bayes Classifier

The concept of Naive Bayes classifier is also called Bayesian classification. It is based on Bayes' theorem. It assumes that all the features are independent and will not influence the estimation process. The Naive Bayes classifier assigns the given object y to class $c^* = argmax_c P(c|x)$ by using $Bayes'$ rule as given below:

$$P(c|x) = \frac{P(x|c)P(c)}{P(x)} \tag{3}$$

where $P(c)$ represents the prior probability of a parameter c before having seen the data. $P(c|x)$ is called the likelihood and defined as

$$P(x|c) = \prod_{k=1}^{n} P(x_k|c) \tag{4}$$

D. Artificial neural network (ANN) model

ANN is often used for solving problems such as classification and estimation [6]. In this study, ANN is used for designing the model for classifying web services. ANN contains three layers i.e., input layer, hidden layer and output layer. Here, for input layer, linear activation function is used and for hidden layer and output layer, sigmoidal function or squashed-S function is used.

Neural network can be represented as:

$$Y' = f(W, X) \tag{5}$$

where X, Y$^{'}$ are the input and output vector, and W is the weight vector associated with the network. The weight vector W is updated in every iteration so as to reduce Mean Square Error (MSE). Weighted vector W is updated as:

$$W_{k+1} = W_k - \alpha G_k \tag{6}$$

where

- W_{k+1}, and W_k are the updated and current weights respectively.
- y and y$^{'}$ are the actual and expected output respectively.
- G_k the gradient vector is defined as:

$$G = \frac{\partial E_k}{\partial W} = \frac{\partial \frac{1}{2}((y'_k - y_k)^2)}{\partial W} \tag{7}$$

- α is the learning constant.

E. Multivariate Adaptive Regression Splines (MARS) Technique

Freidman (1991) proposed a non-parametric regression technique called multivariate adaptive regression splines (MARS) to models with complex relationship [4]. The concept of MARS is based on divide-and-conquer approach, which divide the data into separate region, each of which gets its own regression equation.

Multivariate adaptive regression splines can be expressed using following equation:

$$Y = \sum_{i=1}^{m} C_i BF_i(X) \tag{8}$$

Where Y, X, C_i, and $BF_i(X)$ are dependent variable, independent variable, constant coefficient, and basis functions

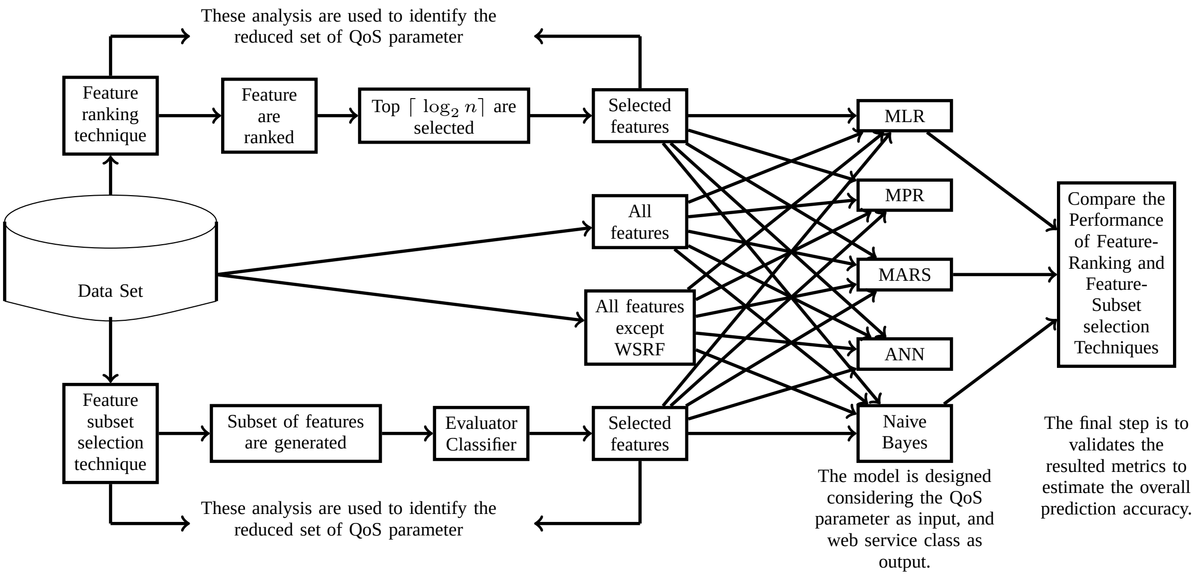

Fig. 1: Framework of proposed work

respectively. Each basis function can be expressed in three different forms:

- Constant value i.e., intercept.
- High function: hinge function has the form $\max(0, x-constant)$ or $\max(0, contant - x)$. It automatically selects variables and values of those variables for knots of the hinge functions. Knots are the points where behavior of the modeled function changes.
- Last one is product of two or more hinge functions.

VI. Analysis of Results

In this section, the relationship between value of QoS parameter and the classes of web service is determined. QoS parameters are considered as input nodes and the output is the class of the web service (Platinum, Gold, Silver, and bronze). The whole procedure for selecting subset of QoS parameter to design a model for classification of web services is shown in figure 1.

The following are the steps followed for selecting subset of QoS parameters to design a model for classification of web services. Each of feature selection technique (both feature ranking and feature subset selection) is applied on QWS dataset. Therefore, a total of 50 ((8 feature selection technique + 1 considering all features+ 1 considering all features without considering WSRF) * five different classification technique) distinct prediction models are built in the study.

Step1. In this paper, nine different number of QoS parameters have been considered to design a model for classifying the web services.

Step2. Further, four feature ranking techniques have been applied on QWS dataset. Each technique will use different performance parameter to rank the features. Further top $\lceil \log_2 n \rceil$ parameters out of n QoS parameters have been considered to design a model for classifying the web services.

Step3. Also four feature subset selection techniques have been also applied on QWS dataset. Each feature subset selection find suitable subsets of feature that collectively have good predictive capability.

Step4. All nine QoS parameters, and subsets of QoS parameters obtained from above steps are evaluated using five different classification techniques i.e., MLR, MPR, Naive Bayes, ANN, and MARS. After completion of first three steps, various selected subsets of QoS parameters have been considered as input of classifier to design a model for QoS parameter.

Step5. The final step compares the performance of all parameters, feature ranking techniques and feature subset selection technique by using different performance evaluation parameters and also validates the resulted parameters to estimate the overall prediction accuracy.

A. *Multivariate adaptive regression splines (MARS) Technique*

In this paper, ten different subsets of QoS have been considered as input to design a model for classifying the web services using multivariate adaptive regression splines (MARS). The prediction accuracy of the MARS models are evaluated and compared using MLR, MPR, NAive Bayes, and ANN. To carry out this work, a computing system with a Core i5 processor having 2GB RAM, a storage memory of 250GB has been utilize. All the prediction models were designed using the *MATLAB* environment. Table **??** shows the mapping of these abbreviations to their actual names. Table III shows the MARS equation for QWS dataset i.e., relation between web-service classes and QOS parameter. The performance parameters for this analysis can be determined based on the confusion matrix as shown in Table IV.

TABLE III: MARS Equation for QWS

Techniques	Equation
AP	Output Class =3.942 +1.5959*max(0, 0.35714 -WSRF) +4.2952*max(0, 0.78571 -WSRF) +0.074974*max(0, WSRF -0.35714) * max(0, DOC-0.020833) -3.4673*max(0, 0.68571 -WSRF) -23.028*max(0, 0.57143 -WSRF)
AP9	Output Class =0.83656 -0.43979* max(0, REL -0.38235) +0.56083* max(0, 0.8913 -SA) -0.36711* max(0, DOC -0.052083)+1.6079* max(0, 0.052083 -DOC) -0.61041* max(0, TP -0.15646) +0.21538* max(0, LT -0.0053903) -76.262* max(0, 0.0053903 -LT) +0.97274* max(0, 0.38235 - REL) * max(0, SA -0.42391)-2.4154* max(0, 0.38235 - REL) * max(0, 0.42391 -SA) -4.6807* max(0, 0.15646 -TP) * max(0, 0.3913 -SA) +0.46846* max(0, DOC -0.052083) * max(0, 0.86047 -AV) -0.13366* max(0, CP -0.66667) +0.088621* max(0, 0.66667 -CP) +121.97* max(0, 0.0053903 -LT) * max(0, REL-0.75708) +137.16* max(0, 0.0053903 -LT) * max(0, 0.75708 - REL)
FR1	Output Class = 0.75884 -1.0653* max(0, REL -0.38235) +1.8058* max(0, SA -0.8913) +0.99122* max(0, 0.8913 - SA) -0.64102* max(0, 0.8913 - SA) * max(0, 0.82462 REL) -4.8528* max(0, AV -0.97674) -3.7385* max(0, 0.97674 - AV) * max(0, TP -0.53401) -0.52805* max(0, 0.97674 - AV) * max(0, 0.53401 -TP) -0.56837* max(0, REL -0.38235) * max(0, TP -0.054422)
FR2	Output Class = 0.81737 -0.82983* max(0, TP -0.11224) +536.28* max(0, 0.0056531 -LT) * max(0, REL -0.8268) +0.33213* max(0, 0.58606 -REL) -158.06* max(0, 0.58606 -REL) -18.493* max(0, 0.11224 -TP) * max(0, 0.071542 -LT)
FR3	Output Class = 0.78995 -0.46037* max(0, SA -0.38235) +0.52399* max(0, 0.8913 -REL) -32.469* max(0, SA -0.38235) * max(0, 0.030323 -RT) -0.71563* max(0, 0.8913 -REL)* max(0, 0.47603 -SA) -5.2503* max(0, AV -0.96512) +1.1765* max(0, 0.96512 -AV) * max(0, SA-0.54684)+53.931* max(0, AV -0.96512) * max(0, REL-0.86957) +17.624* max(0, AV -0.96512) * max(0, 0.86957 -REL) +8504.1* max(0, REL -0.8913) * max(0, 0.0028345 -RT) +615.25* max(0, RT -0.0017081) * max(0, SA-0.83224)
FR4	Output Class = 1.0179 -2.8514* max(0, PC1 -0.68259) -0.8066* max(0, PC3-0.44608) +0.21212* max(0, PC2-0.043041) -19.985* max(0, 0.043041 -PC2) +34.92* max(0, 0.44608 -PC3) * max(0, PC1 -0.89271) +41.223* max(0, 0.043041 -PC2) * max(0, PC1-0.75027) +23.253* max(0, 0.043041 -PC2)* max(0, 0.75027 - PC1) -1.0129* max(0, 0.48958 -PC1) +5.0753* max(0, 0.48958 -PC1) * max(0, 0.67486 -PC1) +53.174* max(0, 0.043041 -PC2)* max(0, 0.56832 -PC3)-121.39* max(0, 0.44608 -PC3) * max(0, 0.023056 -PC2) +12.568* max(0, PC1 -0.68259) * max(0, PC4 -0.89454) +2.5758* max(0, PC1 -0.68259) * max(0, 0.89454 -PC4)
FS1	Output Class = 0.78502 -1.2486* max(0, 0.13605 -TP) +0.43841* max(0, 0.95652 -SA) +0.70406* max(0, TP -0.13605) * max(0, CP-0.33333) +838.01* max(0, AV-0.97674) * max(0, 0.69565 -SA) +0.71139* max(0, 0.95652 -SA) * max(0, TP -0.054422) -79.508* max(0, 0.95652 -SA) * max(0, AV -0.98837) -785.53* max(0, AV-0.97674) * max(0, 0.68478 -SA) -1.3453* max(0, TP -0.0068027)
FS2	Output Class = 0.86972 -0.64605* max(0, REL -0.38235) +0.32441* max(0, 0.38235 -REL) +0.72422* max(0, 0.8913 -SA) -0.34535* max(0, DOC -0.052083) +1.4456* max(0, 0.052083 - DOC) -0.59693* max(0, TP -0.15646) +0.32692* max(0, 0.15646 - TP) +0.17425* max(0, LT-0.0053903) -74.545* max(0, 0.0053903 -LT)-6.0424* max(0, 0.15646 -TP) * max(0, 0.3913 -SA) +0.42841* max(0, DOC -0.052083) * max(0, 0.86047 -AV) +144.04* max(0, 0.0053903 -LT)* max(0, REL-0.74728) +142* max(0, 0.0053903 -LT) * max(0, REL-0.74728) * max(0, 0.74728 -REL) -0.73426* max(0, 0.8913 -SA) * max(0, 0.80719 -REL)
FS3	Output Class = 0.81274 +0.63714* max(0, 0.8913 -SA) -0.40648* max(0, DOC -0.052083) +1.3594* max(0, 0.052083 - DOC) -0.54941* max(0, TP -0.15646)-35.871* max(0, 0.0064088 RT) +0.63707* max(0, 0.38235 -REL) * max(0, SA-0.42391) -2.7238* max(0, 0.38235 -REL) * max(0, 0.42391 -SA) +0.62725* max(0, DOC -0.052083) * max(0, REL -0.7037) +0.34279* max(0, DOC -0.052083) * max(0, 0.7037 -REL) -4.408* max(0, 0.15646 -TP) * max(0, 0.3913 -SA) -9.1094* max(0, REL -0.38235) * max(0, 0.06385 -RT) +0.26326* max(0, DOC -0.052083) * max(0, 0.80233 -AV)
FS4	Output Class = 0.87071 -8.4136* max(0, AV -0.98837) +0.34092* max(0, 0.98837 -AV) -0.54193* max(0, DOC-0.35417) +0.36281* max(0, 0.35417 -DOC) -0.33952* max(0, TP -0.010204) -11.656* max(0, 0.010204 -TP) -21.335* max(0, REL -0.38235) * max(0, 0.032286 -RT) -0.36666* max(0, CP -0.66667) +0.1501* max(0, 0.66667 -CP)+0.66186* max(0, 0.38235 -REL) * max(0, AV-0.45349) -2.5628* max(0, 0.38235 -REL) * max(0, 0.45349 - AV) +2.6934* BF8 * max(0, 0.59459 -BP) +0.94725* max(0, DOC-0.35417)* max(0, AV-0.83721) +0.84849* max(0, DOC-0.35417) * max(0, 0.83721 -AV) -32.322* max(0, 0.0058238 -RT)

TABLE IV: Confusion Matrix

AP				
	C1	C2	C3	C4
C1	41	0	0	0
C2	0	100	0	0
C3	0	0	120	0
C4	0	0	0	103

AP9				
	C1	C2	C3	C4
C1	37	4	0	0
C2	1	92	7	0
C3	0	5	113	2
C4	0	0	12	91

FR1				
	C1	C2	C3	C4
C1	26	15	0	0
C2	2	61	37	0
C3	1	14	96	9
C4	0	0	31	72

FR2				
	C1	C2	C3	C4
C1	16	23	2	0
C2	6	46	48	0
C3	0	34	66	20
C4	0	2	55	46

FR3				
	C1	C2	C3	C4
C1	28	13	0	0
C2	5	61	34	0
C3	0	22	90	8
C4	0	0	29	74

FR4				
	C1	C2	C3	C4
C1	32	9	0	0
C2	2	80	18	0
C3	0	11	99	10
C4	0	0	22	81

FS1				
	C1	C2	C3	C4
C1	21	17	3	0
C2	2	51	47	0
C3	0	26	83	11
C4	0	2	45	56

FS2				
	C1	C2	C3	C4
C1	38	3	0	0
C2	4	84	12	0
C3	0	6	113	1
C4	0	0	6	97

FS3				
	C1	C2	C3	C4
C1	36	5	0	0
C2	4	84	12	0
C3	0	6	113	1
C4	0	0	16	87

FS4				
	C1	C2	C3	C4
C1	37	4	0	0
C2	0	88	12	0
C3	0	6	114	0
C4	0	0	18	85

TABLE VI: Used Naming Conventions for different Techniques

Abbreviation	Corresponding Name
AP	All QoS parameter
AP9	All QoS parameter without considering WSRF
FR1	Chi Squared test
FR2	Gain Ratio Feature Evaluation
FR3	Information Gain Feature Evaluation
FR4	PCA
FS1	Classifier Subset Evaluation
FS2	Consistency Subset Evaluation
FS3	Filtered Subset Evaluation
FS4	Correlation based Feature Selection

Table V, shows the obtained performance metrics for QWS dataset using different techniques. From Table V, it can be concluded that the performance MARS technique is better as compare with other four techniques. It has better value of accuracy, AUC, and F-Measure.

B. *Feature selection techniques*

In this study, eight different type of feature selection techniques have been considered for finding subsets of QoS parameters. The selected subset of QoS parameter from different feature selection techniques are presented in Table VII.

TABLE VII: Selected subset of QoS parameter from different feature selection techniques after removing WSRF

Technique	Selected QoS parameter
Chi Squared test	AV, TP,SA, REL
Gain Ratio Feature Evaluation	RT, TP, REL, LT
Information Gain Feature Evaluation	RT, AV, SA, REL
PCA	PC1, PC2, PC3, PC4
Classifier Subset Evaluation	AV, TP, SA, CP
Consistency Subset Evaluation	RT, AV, TP, SA, REL, LT, DOC
Filtered Subset Evaluation	RT, AV, TP, SA, REL, DOC
Correlation based Feature Selection	RT, AV, TP, REL, CP, BP, DOC

1) Feature ranking technique: In this study, four different type of feature ranking techniques have been considered for finding subset of QoS parameters based on their ranking.

TABLE V: Performance matrix

Techniques	Accuracy (%)					AUC					F-Measure (%)				
	MLR	MPR	Naive Bayes	ANN	MARS	MLR	MPR	Naive Bayes	ANN	MARS	MLR	MPR	Naive Bayes	ANN	MARS
AP	92.03	87.64	81.87	93.68	100	0.9784	0.9753	0.9756	0.9885	1	92.03	87.64	81.87	93.68	100
AP9	79.67	79.95	54.95	80.77	91.48	0.9480	0.9510	0.8682	0.9552	0.9689	79.67	79.95	54.95	80.77	91.48
FR1	62.64	64.84	56.87	54.12	70.05	0.9047	0.9119	0.8748	0.8796	0.9009	62.64	64.84	56.87	54.12	70.05
FR2	64.56	57.69	54.95	56.32	69.51	0.9024	0.9005	0.8742	0.8966	0.9135	64.56	57.69	54.95	56.32	69.51
FR3	50.27	42.86	48.08	40.93	47.80	0.8310	0.7787	0.8324	0.7465	0.8094	50.27	42.86	48.08	40.93	47.80
FR4	69.23	62.64	54.95	68.96	80.22	0.9334	0.9448	0.8459	0.9275	0.9289	69.23	62.64	54.95	68.96	80.22
FS1	54.95	64.84	55.22	55.77	57.97	0.8442	0.9119	0.8273	0.8460	0.8446	54.95	64.84	55.22	55.77	57.97
FS2	78.30	76.37	53.30	83.52	91.21	0.9436	0.9529	0.8599	0.9615	0.9840	78.30	76.37	53.30	83.52	91.21
FS3	78.57	78.57	60.16	80.22	87.91	0.9457	0.9679	0.9039	0.9557	0.9606	78.57	78.57	60.16	80.22	87.91
FS4	77.75	76.92	60.71	78.57	89.01	0.9415	0.9523	0.9154	0.9494	0.9578	77.75	76.92	60.71	78.57	89.01

Subsequently, these selected subset of QoS parameters are considered as input to design a prediction model using five different classification techniques. The performance of each prediction model is evaluated in terms of three different performance parameters i.e., Accuracy, AUC, and F-Measure. Table V shows the performance matrix for each of the cases. From Table V, it can be inferred that feature ranking using PCA compute the best set of QoS for classifying web services as compare with other three techniques.

2) Feature subset selection techniques: In this study four different type feature subset selection techniques are used to find suitable subset of features which collectively have good predictive capability. Table V shows the performance matrix for feature subset selection techniques. From Table V, it can be inferred that feature subset selection using consistency subset evaluation computes the best set of QoS for classifying web services as compared with other three techniques.

C. Discussion

This subsection summarizes the results of an empirical investigation over the QWS dataset. Table V shows the accuracy, AUC, and F-Measure values of prediction models which were designed by considering different subsets of QoS parameters. Form Table V, it can be observed that the models designed by considering WSRF as input, passes the desired prediction accuracy as comparable with the other. Accuracy with WSRF for MARS model is maximum i..e, 100 %, where the accuracies without WSRF is 91.48 %. Based on these study, we answer our earlier research questions.

RQ1 In this study, ten subset of QoS parameters have been considered as input to design a model for classifying the web services using five different classification technique i.e., MLR, MPR, Naives Bayes, ANN, and MARS. Table V shows the performance matrix of the perdition model. From these tables, it can be observed that QoS parameters were significantly correlated with maintainability of web service.

RQ2: In this study, eight different feature selection techniques have been considered to find the reduced subset of QoS parameters. From Table V, it is clear that there exists a reduced subset of QoS parameters for some classifiers which are more helpful designing a prediction model as compared to considering all nine QoS parameters. In case of Naive Bayes classifier, the model designed by considering reduced set of QoS parameter using FR1, FS3, and FS4 as input, give better result as compared to the result obtained by considering all nine QoS parameters.

RQ3: In this study, four different type of feature ranking techniques have been considered to find the reduced subset of QoS parameters. From Table V, it is clear that feature selection using PCA feature ranking technique yields the best results for MARS classification technique.

RQ4: In this study, four different type of feature subset selection techniques have been considered to find the reduced subset of QoS parameters. From Table V, it is clear that feature selection using consistency subset evaluation yields the best results for MARS classification technique.

RQ5: From Table V, it was found that the performance of the feature selection techniques is varied with the different classification techniques used. This shows that selection of classification technique to design a prediction model for classifying the web services affect the feature selection techniques.

VII. Comparison of models

Figure 2 shows the box-plot diagrams for each of the cases. The figure contained five different type of box-plots, one for each classifier. Since, in this study five different type of classification techniques and three different performance parameters have been considered for classification of web service. Therefore, fifteen different box-plot diagrams have been displayed (one for each combination). This box-plot diagrams help to observe performance of all techniques on a single diagram. From the box-plot diagram, it is evident that MARS technique present best performance as compared to other techniques. It has the highest median and max values as compare to other techniques.

Apart from the comparative analysis done to find the suitable model for classification of web service, this paper also makes the comparison of the proposed work with the work done by Mohanty et al. [8] [7]. Mohanty et al. have used same dataset for classification of web service based on different techniques. They have considered accuracy as a performance parameter to compare the models. Table VIII shows the accuracy (%) value of the proposed work and the work done by Mohanty et al.. From Table VIII, it can be observed that, in case of model designed without removing WSRF, accuracy value is almost same, but in case of model designed

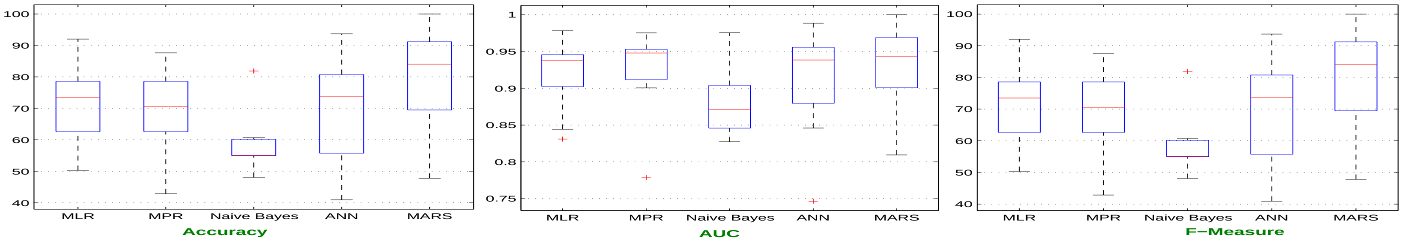

Fig. 2: Box-Plot Analysis of the Classification Techniques

after removing WSRF, the proposed approach obtained better accuracy as compared to others techniques.

TABLE VIII: Performance based on Accuracy (%)

MMRE			
Author	Technique	AP	AP9
Mohanty et al. [8]	PNN	97.22	-
	BPNN	99.72	86.11
	GMDH	100	67.77
	J48	100	73.61
	TreeNet	99.72	86.61
	CART	99.72	79.44
	SVM	63.33	60.55
Mohanty et al. [7]	Naives Bayes	85.62	75.01
	Taby search	82.45	65.48
	Markov blanket	81.36	71.38
Proposed Work	MARS	100	91.48

VIII. Threat to Validity

For the sake of completeness, some of the existing threats to validity of the proposed work have been considered. The proposed work may suffer from following threats:

i. The results obtained are based on the historical data of web service, which have specific characteristics and behavior. Hence, they could not be generalized.

ii. Only nine QoS parameters are used to design a model. Some of the QoS which are widely used for selection of web service can be further considered for classification of the web services.

iii. Number of psychological factors also affect web service. But in this study, these are not considered such as different level of expertise for developers, standards in which software is developed, types of developers involved, history of development of the system and other stockholders of the system.

IX. Conclusion

In this paper, an attempt has been made to use QoS parameters in order to design a model for classifying the web services. Experiment was carried out for QWS dataset by using MATLAB environment. Multivariate adaptive regression splines (MARS) were used to design a model for classifying the web services. The QoS parameter were taken as requisite input data to train the models and estimate the class of web service i.e., platinum, gold, silver, and bronze. Performances of the MARS models were compared with those of the multivariate linear regression models, multivariate polynomial regression, Naives Bayes classifier, and artificial neural network models. The results show that the MARS models can effectively help on classifying the web services.

This paper also focuses on a comparative study of different feature reduction technique to identify a subset of QoS parameters which may be better correlated with web service class. From result, we can observe that there exists a reduced subset of QoS parameters for some classifiers which help effectively to design a prediction model as compared to considering all nine QoS parameters.

Further, work can be replicated on the usage of hybrid approach of neural network models for classification of web service.

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