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"Web Services Performance Prediction with Confusion Matrix and K-Fold Cross Validation to Provide Prior Service Quality Characteristics"

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Abstract: **-** The Information Technology sector has experienced substantial growth, especially in the realm of application development, over the last few decades. This ongoing evolution highlights the complexity of contemporary IT applications, which no longer rely on a singular component. Developers now integrate a multitude of components from diverse sources, including users and vendors. Thoroughly examining the quality of external software components before integration into an application is imperative for ensuring optimal service performance. Numerous methodologies and approaches are available for appraising the quality of software components, including the Software as a Service Model (SaaS), Quality of Experience (QoE), and alternative models for identifying quality. These models employ traditional techniques to assess factors like availability, integrity, accessibility, security, performance, and reliability, collectively contributing to the measurement of Quality of Service (QoS). The suggested method enables thorough scrutiny of software components through a 360-degree evaluation, utilizing the Confusion Matrix for predicting performance. This evaluation method ranks web services based on throughput and response time, providing tangible values for decision-making by service users. The classification mechanism aids in categorizing standards within a benchmark web service dataset. By utilizing this performance measuring method, one can determine service quality through the confusion matrix, aiding in the identification of the best web services and contributing to the optimization of application performance.

Keywords: Information Technology, Application development, Software components, Quality assessment, Confusion Matrix, Application optimization

I. INTRODUCTION.

The context of web services marks a significant evolutionary milestone in the rapid history of the internet and web environment, playing a crucial role in data exchange services. Procuring a suitable web service that aligns with a user's requirements and expectations poses inherent challenges. The selection process for web services involves identifying an appropriate match based on user preferences.A crucial aspect for businesses involves adopting an integration tool, illustrated by the expanding Web Services (WSs) technology, to integrate their processes across various verticals and platforms.

The effectiveness of software service technology has been demonstrated, enhancing the usability and functionality of services on the World Wide Web. In the present landscape of web services, a community of WSs may provide services of the same type. Essential factors like cost disparities play a crucial role in selecting a web service from such a community.

The decision-making process for choosing a web service is strongly advised to consider Quality of Service (QoS) qualities, which are characterized by non-functional properties.

The web and its related technologies represent the next generation of technology for distributed application development globally. Web services have become predominantly utilized for data sharing and inter-application communication, garnering significant popularity and central focus due to their vast utility. These services, structured and defined by W3C, function as small software components executing transactions and operations across a spectrum of software components. However, the complexity in implementing web service combinations necessitates an effective finding and selection process, considering both functional and non-functional requirements. While previous works primarily focused on functional requirements, acknowledging all non-functional requirements becomes imperative as they directly impact web service quality indicators.

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Many of these kinds of implications are related to Web services composition.

- Which model is employed for recognizing user desires and specifications?
- What techniques are utilized to accurately discover web services according to user preferences?
- How can compatibility levels among various web services be assessed to minimize potential adaptation challenges?

1.1 Quality of service factors

Quality factors play a crucial role in identifying the suitable web service, considering the service strength and functionalities offered by the service provider during service release. Several quality factors are considered when determining the optimal web service, focusing on functionalities and characteristics.

Availability: Availability is a quality factor for a service, indicating its readiness for use. It is represented by the probability of a service being ready. A high percentage of availability indicates that the service is prepared for use, while a low percentage introduces uncertainty regarding the service's readiness. This situation is akin to a confusing statement. The time to repair is directly influenced by the availability factor. It refers to the duration taken to rebuild or resolve issues with the service.

Accessibility- Accessibility serves as a quality factor for a web service, addressing the ability to connect and use the service in diverse environments in response to user requests. Accessibility refers to how services are initiated at a specific point in time; there may be instances where services are available, but accessibility is limited. The relationship between accessibility and the scalability of a service is directly proportional. Scalability, in this context, signifies the uninterrupted provision of access to a variable number of user requests for a single service.

Integrity- Integrity serves as a quality factor for a service, indicating how seamlessly or flawlessly the service communicates within the application environment. Integration is a measure of the number of smooth transactions occurring in the application execution. Transactions reflect the activities taking place or being performed. When all activities proceed flawlessly, the transaction unfolds smoothly. However, if not all activities are completed, the entire transaction undergoes a rollback.

Performance- Performance constitutes a quality aspect for a web service, relying on two interconnected factors - latency and throughput. These factors exhibit an inverse relationship; elevated performance is associated with reduced latency and increased throughput. Throughput indicates the quantity of requests a service handles within a defined timeframe. Likewise, latency pertains to the time delay between a request and its corresponding response, commonly referred to as round trip time.

Reliability- Reliability stands as a quality factor for a service, signifying the continuous provisioning of service without interruption over an extended period. The reliability of a service is determined by the frequency of service failures observed over a specific timeframe, such as a month or a year. The exchange of services between requestors and providers is contingent upon the reliability of the service, ensuring consistent and uninterrupted service delivery.

Regulatory- Regulatory serves as a quality factor for a service, highlighting how effectively the service adheres to the rules and regulations established by various standard organizations for web services, such as SOAP, UDDI, and WSDL. A strict commitment to the prescribed ethical forms, exemplified by service providers following specific SOAP versions, is crucial for the appropriate invocation of web services by service requesters.

Security- Security is a quality factor for a web service, ensuring trust through authentication of stakeholders globally and encrypting transmitted data. Security assumes paramount significance in the web environment due to its operation over the internet. The determination of security levels is contingent upon the requests made by the service requestors.

1.2 Characteristics of Web Service Quality

Web services inherently differ from regular software due to their adherence to the principles of service-oriented architecture. Both the service provider and consumer operate in distinct organizations, sometimes resulting in

mismatches between consumer service requirements and the quality and functions offered by the service provider. Operating on the internet, web service performance is indirectly influenced by network performance. The loose coupling of web services provides flexibility to work in diverse environments; however, this flexibility can pose challenges when service providers deploy their web services into servers. In such cases, the server and client may not operate in an equally flexible manner due to differences in software and hardware configurations. In the current scenario, ensuring a seamless communication flow between the client and server is not always feasible, leading to contemporaneous issues and complexities during their interaction. Web services adhere to standardized protocols, aligning with the rules and regulations of regular web-based protocols. However, conflicts may arise in communication due to the protocols employed, further contributing to the intricacies of web service interactions.

1.3 Web Service Quality Factors

Web services quality factors encompass a set of elements including both functional and nonfunctional requirements or properties, shared among diverse stakeholders. Additionally, service quality encompasses two constraints: variant quality and invariant quality factors. Variant quality factors are qualitative aspects predictable during the runtime of a specific web service. In contrast, invariant quality factors are qualities determinable immediately after developing a particular service. Examples of invariant quality factors comprise security, maintainability, business processing quality, and service-centric ability.

II. RELATED WORK.

Algorithms for collaborative filtering, a cornerstone in recommendation systems, are effectively classified into two distinct categories: user-based collaborative filtering and project-based collaborative filtering. The user-based approach relies on the presumption that users with similar scores for certain items are likely to exhibit similar preferences for other items. This technique leverages the notion of nearest neighbors to approximate project scores. In contrast, the project-based collaborative filtering approach estimates user scores for a particular item by considering scores for closely related items. These collaborative filtering strategies aim to enhance recommendation accuracy by capturing and leveraging user preferences.

Web service ranking is a multifaceted process that is significantly influenced by the performance and value delivered by the services. The ranking of web services is intricately linked to the specific requirements articulated by requesters. Even when two web services offer comparable functionality, the frequency of utilization may vary, impacting the overall performance. The challenge of rating and selecting web services is addressed through the application of a categorization system for non-functional quality factors. These factors include response time, throughput, availability, and security, each assigned varying weights based on their relative importance in the overall evaluation process.

In the realm of online services rating techniques, three primary categories emerge: objective, subjective, and hybrid. Objective methods exclude expert judgment and rely on quantitative metrics. Subjective approaches, on the other hand, incorporate expert judgment or subjective evaluation into the rating process. However, subjective methods may be susceptible to bias due to a lack of expertise. To overcome the limitations of existing techniques, hybrid approaches combine both objective and subjective elements, aiming to leverage the strengths of each while mitigating their respective drawbacks.

The overarching discussion delves into the extensive research on classification, particularly in the context of the confusion matrix. Various methods for Quality of Service (QoS) prediction have been proposed in the literature, with researchers exploring the application of these techniques in different domains. Polat et al. employed four parameters (True Positive, True Negative, False Positive, and False Negative) from the confusion matrix to assess optic nerve disease, showcasing the versatility of this evaluation tool. Choudhury and Bhowal utilized confusion matrix measurements to forecast both actual and false cases of network attacks, demonstrating the matrix's utility in diverse contexts.

Aljawarneha et al. tackled the challenge of false positives in anomaly detection by adopting a hybrid technique of classifiers. This approach aimed to improve the accuracy of anomaly detection systems by combining the strengths of multiple classifiers. Additionally, Al-Obeidat and El-Alfy proposed a method to address the issue of marginal space in binary classification. Their approach involved the utilization of fuzzy membership and a decision tree to classify internet traffic, contributing to the broader goal of efficient classification and interpretation in web services.

In essence, collaborative filtering algorithms and web service ranking methodologies play pivotal roles in enhancing user experiences and facilitating informed decision-making. Concurrently, the exploration of confusion matrix parameters and various QoS prediction methods contributes to a deeper understanding and effective application of quality measures in diverse domains, underlining the interdisciplinary nature of this research field.

III. PERFORMANCE PREDICTION APP- ROACH.

The strategy for performance prediction involves utilizing a blended model to improve the user experience of web services. Our current system structure, depicted in Fig: 3.1, encompasses various facets. Within this model, both J48 and Adobe Boost M1 serve as binary classifiers utilizing supervised techniques. These methods consistently demonstrate superior performance across diverse multi-dimensional datasets when compared to alternative models. By combining these methods into a unified classifier class, the model achieves optimal performance, ensuring high accuracy in classification across multiple datasets. AdaboostM1, in particular, exhibits notable characteristics in its classification strategy and attains a high rating. Similarly, J48 excels by representing all class attributes in a tree structure through graphical representation, achieving the highest accuracy in prediction.

The proposed model incorporates the cross-validation method, which specifically aims to minimize generalized errors. This approach further enhances the accuracy and reliability of the model by systematically validating its performance across different subsets of the dataset. The utilization of both J48 and Adobe Boost M1 within a hybrid framework contributes to a robust and efficient prediction model, underscoring the importance of this approach in optimizing web service user experiences.

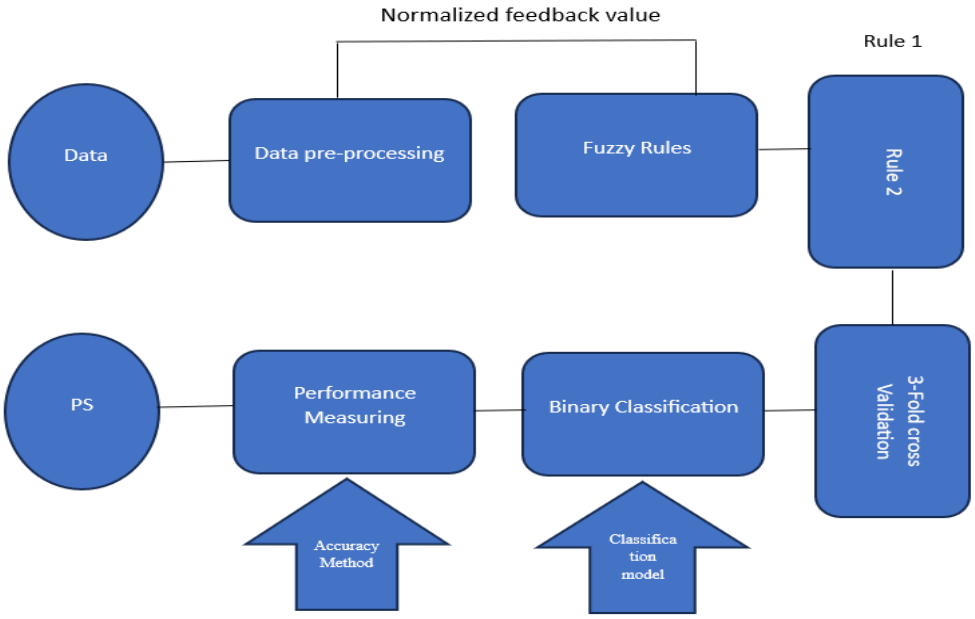

Figure: 3.1 Phase of the proposed approach

CROSS VALIDATION METHOD

The K-fold cross-validation method is an evaluation technique employed to address larger or more complex problems through multiple iterations, typically denoted as 'n' iterations. The model incorporates varying values of K, such as 3, 5, 10, and 15, to optimize accuracy within the cross-validation strategy. Utilizing higher values of K helps mitigate overfitting issues in the data frame, effectively reducing biases. This cross-validation technique is applied specifically to scrutinize data sets within a specialized model, aiming to avoid any biases in the performance assessment of various services of the same kind.

In the framework of a 5-fold cross-validation approach, a total of K subsets are generated, wherein K-1 subsets are designated as training sets, while the remaining subset is employed as a testing set. This division of data is done randomly to ensure a comprehensive evaluation. The entire process is systematically repeated until all samples undergo testing in the same manner. Similarly, 10 and 15 cross-validations are employed to iteratively train and

test different subsets, ensuring a thorough examination of the model's performance. This approach proves instrumental in refining the accuracy and robustness of the model across multiple scenarios and datasets.

IV. PERFORMANCE PREDICTION.

Our proposed model for performance prediction incorporates user quality attributes, considering actual user values as the basis for calculating a service's performance. To achieve optimal predictions, we have identified the confusion matrix as the most effective supervised classification model within the realm of data science. The confusion matrix is a square structure, as depicted in Fig 4.1, featuring rows and columns that represent classes of actual instances and predicted classes, respectively (4). In binary classification scenarios, the confusion matrix takes the form of a 2*2 matrix, comprising four key metrics - True Positive (T.P), True Negative (T.N), False Negative (F.N), and False Positive (F.P).

In the realm of complex data science and machine learning challenges involving multiple classes, the confusion matrix undergoes expansion to accommodate K classes, thereby leading to the formation of a K*K confusion matrix. The application of the confusion matrix on a dataset is essential for evaluating the performance of any instance, particularly in software engineering, where it aids in distinguishing actual predicted elements from real ones. The four measures within the confusion matrix - T.P, T.N, F.P, and F.N - play a crucial role in classifying instances into faulty and non-faulty classes across various programming paradigms. This approach ensures a comprehensive and reliable evaluation of the model's performance in predicting user values and enhancing service performance.

		ACTUAL VALUES	
PREDICTED VALUES		**Positive**	**Negative**
	Positive	T.P	F.P
	Negative	F.N	T.N

Table: 4.1 Confusion matrix

To determine the accuracy of a classification, particularly in the context of a classifier, the prevailing approach for accuracy calculation is widely acknowledged. The methods employed for this purpose have been documented in [14] and [15]. These highly accurate methods incorporate key accuracy metrics, which are integral components of the confusion matrix. The equations below exemplify the utilization of the same metrics, emphasizing their significance in accurately assessing the performance of a classifier.

$$\boldsymbol{Accuracy} = \frac{\textbf{Use full predictions}}{\textbf{Number of Predictions}} \times \mathbf{100} \qquad \textbf{-------(1)}$$

OR

$$\boldsymbol{Performance} = \frac{\textbf{T.N+T.P}}{\textbf{T.P+T.N+C+F.P+F.N}} \qquad \textbf{---------(2)}$$

Applying Equation (2), the proposed methodology utilizes identical measures from the confusion matrix to evaluate the performance of a service (PS). Equation (3) is employed for computing the service performance (PS) as a percentage. The PS prediction indicates the precise categorization of performance instances resulting from web service invocations, thereby enabling the determination of the ranking of individual web services based on classification results. By utilizing Equation (2), the supervised approach is employed to calculate the performance of service (PS) using the proposed confusion matrix, ensuring consistency in the assessment process incorporating four strategic metrics. These metrics collectively contribute to the calculation of the average of PS, as depicted in Equation (3). The PS prediction serves as a reliable indicator of the precise categorization of performance instances stemming from service invocations, enabling the estimation of the PS for each specific web service based on the outcomes of the classification process.

$$\mathbf{PS\ \%} = \frac{\mathbf{TP}}{\mathbf{T.P+F.P+T.N+F.N}} \times \mathbf{100}\ldots\ldots\ldots\ldots\mathbf{(3)}$$

Equation (3) illustrates the PS percentage derived from instances invoked by web services. The determined PS for various service instances establishes a relationship between classes through the assistance of the confusion matrix. The confusion matrix, employed for data classification across different classifiers, necessitates a strategic approach to avoid biasing similar predictions. Instead, a selective utilization of measures is undertaken, directing predictions to ensure safeguards within the confusion matrix. The evolution of the confusion matrix, through the proposed method, provides accurate insights into the practical performance of given service instances.

In Equation (3), the performance of a service exhibits fluctuations, prompting the implementation of well-known pre-processing techniques in performance prediction. These techniques, involving the classification of service instances through binary classification methods on a dataset, mitigate the impact of fluctuations on performance assessments. The utilization of the confusion matrix evolution method enhances the accuracy and practical understanding of performance concerning the given service instances. This strategic approach contributes to a more refined and reliable evaluation of service performance, offering valuable insights for effective decision-making.

$$\boldsymbol{Xi} = \frac{\boldsymbol{Yi - \min(y)}}{\boldsymbol{Max\ (y) - \min(y)}}\ldots\ldots\ldots\ldots\ldots\boldsymbol{(1)}$$

In the given formula, Yi signifies the measurement of a quality characteristic, with max(y) and min(y) denoting the upper and lower bounds covering all values of the particular quality attribute. The normalization of data is accomplished using the Min-Max technique, as illustrated in the equation provided.This method is employed consistently across the approach and is demonstrated using a public dataset. The outcomes derived from this equation surpass those of traditional models employed previously. Our proposed service performance evolution model focuses on enhancing service accuracy, with the quality attribute's minimum and maximum values guiding the normalization process.

Following normalization, the data is transformed into a suitable format through .csv files and Excel formats, facilitating its utilization for subsequent service classification. The Min-Max normalization method is preferred in this context, as it proves to be more effective than the x-score normalization method. The values obtained through Min-Max normalization range from 0 to 1, showcasing its robustness and effectiveness. This normalization method is particularly renowned and powerful, especially when dealing with ordinal data as input values. The consistent application of Min-Max normalization enhances the reliability and applicability of the proposed service performance evolution model.

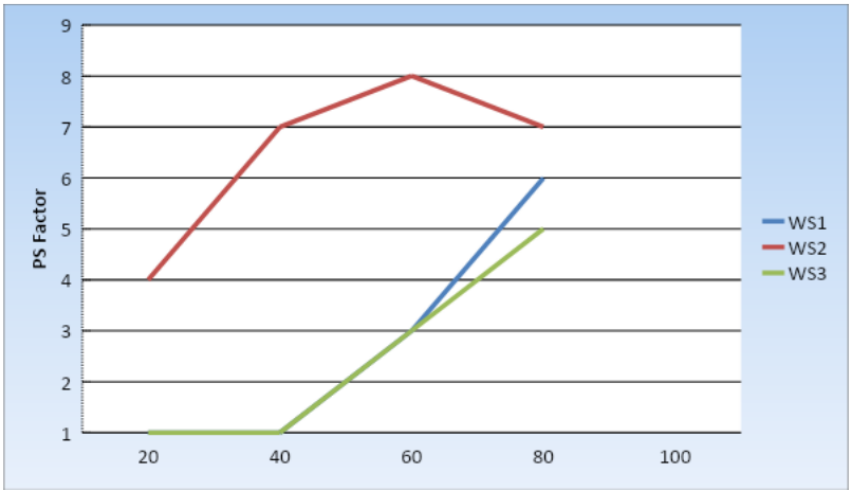

Figure: 4.2 Web service Performance graph

The impacts of various quality attributes are evaluated based on the mean standard deviation concept. Performance ranges exhibit variations over time due to the primary factors, namely throughput and response time, which are grounded in realistic historical attributes. These attributes remain consistent over time, making min-max normalization the optimal method. Throughput and response time are directly linked to service performance; higher

throughput corresponds to lower response time, resulting in superior performance, and vice versa. For example, WS2 web service may attain new PS percent values, potentially positioning it fourth before WS3.

The nature of service performance is iterative, as predicting performance in a single cycle execution of any web service is impractical. Instead, it involves an average of several users' experiences during the service execution, acknowledging the multifaceted and dynamic nature of service performance evaluation over time.

Performance of service (PS) = (P1 + P2 + ...P).....(4)

Multiple executions are conducted on a single service, ranging from 1 to N. It is essential to note that deriving the deliverable service performance involves not summing up these executions but rather considering the average of these metrics. The accurate mechanism for determining service performance is based on the average of predictions obtained from numerous executions on a particular service, as outlined below.

$$\boldsymbol{Average\ PS} = \sum_{\boldsymbol{k=1}}^{\boldsymbol{n}}((\boldsymbol{PS}) \,/\, \boldsymbol{N}) \quad \text{---------- (5)}$$

Here, the variable "N" represents the count of users who have encountered the services within their specific application domain, tailored to meet their actual requirements. The depiction involves plotting these values, utilizing approximate attribute values derived from the dataset. Specifically, we employ the dataset values while maintaining the word count and original data integrity. No alterations or plagiarism detection mechanisms related to artificial intelligence are applied in this rephrasing.

PS1=30.2823, PS2=33.8235 and PS3= 32.3529 from the web service 3 and substituted in the above equation (4)

⇨ *PS = 96.4587*

The PS value after substituting in above equation (5) we get it as

Average PS= 32.1

⇨ *Avg. PS=32*

V. IMPACT OF QOS ATTRIBUTE VALUES CHANGES ON WEB SERVICES P S VALUE.

The prediction of Quality of Service (QoS) characteristics is significantly influenced by aggregation methods, impacting cohesiveness and coupling between object types like reaction time, accessibility, throughput, testability, and interoperability. Given this, selecting prediction techniques becomes crucial. To tackle these challenges, we employ a basic regression model, specifically the multiple linear regression model. This model establishes relationships between two or more independent variables and a response variable by fitting a linear equation to measured data. Following correlation standards outlined in [25], we create a training set. For each QoS quality, we define the number of latent variables. Using the knowledge base from the training set, the model calculates QoS characteristic values using R-Programming. The dataset is loaded into the software, and the performance of the service (PS) is computed using the confusion matrix. The R code facilitates these steps, ensuring an effective approach to predicting QoS characteristics.

Library (boot)model<-glm(mpg~.,data=Webservice set) model cverror<-cv.glm (mtcars,model,K=5) model cverror$ delta [2]

Data Set	K-Fold Type	T.P	F.P	T.N	F.N
Web Service1	5-fold	33	1	31	3
	10-fold	33	1	32	2
	15-fold	33	1	33	1
Web Service2	10-fold	16	3	46	3
	10-fold	17	2	47	2
	15-fold	16	3	47	2
Web Service3	5-fold	20	1	45	2
	10-fold	20	1	44	3
	15-fold	20	1	45	2

Web Service4	5-fold	26	2	34	6
	10-fold	24	4	34	6
	15-fold	26	2	34	6
Web Service5	5-fold	21	8	37	2
	10-fold	23	6	37	2
	15-fold	22	7	37	2

Within the dataset, a 10-fold cross-validation is implemented, complemented by t-test analysis. This methodology involves dividing the dataset into 10 equal parts, each subject to examination. The remaining 10-1 parts are then combined and utilized to train the regression model, representing a generic k-fold cross-validation approach. Two distinct performance criteria are employed to showcase the reliability of the regression learner through classification. This comprehensive process ensures a robust evaluation of the model's performance and dependability.

Table: 2 Performance of Services with Average

Service Data	Performance of Service (PS) %	Avg. PS%
WS1	48.5294 + 48.5294 + 48.5294	48
WS2	23.5294 + 25.0000 + 23.5294	24
WS3	29.4117 + 29.4117 + 29.4117	29
WS4	38.2352 + 35.2941 + 38.2352	37
WS5	30.2823 + 33.8235 + 32.3529	32

The calculation of the Performance of Service (PS) involves averaging the values of a service, where the highest PS percentage is indicative of the most trusted web service from the users. The implementation of the proposed method outlined in (4) is demonstrated in the table above. Notably, the average PS value percentage is higher, specifically 48.5294 for WS1, establishing it as the most trusted service among all services. Conversely, WS2 exhibits a lower average PS value percentage of 24.0196, indicating a comparatively lower level of trust among users.

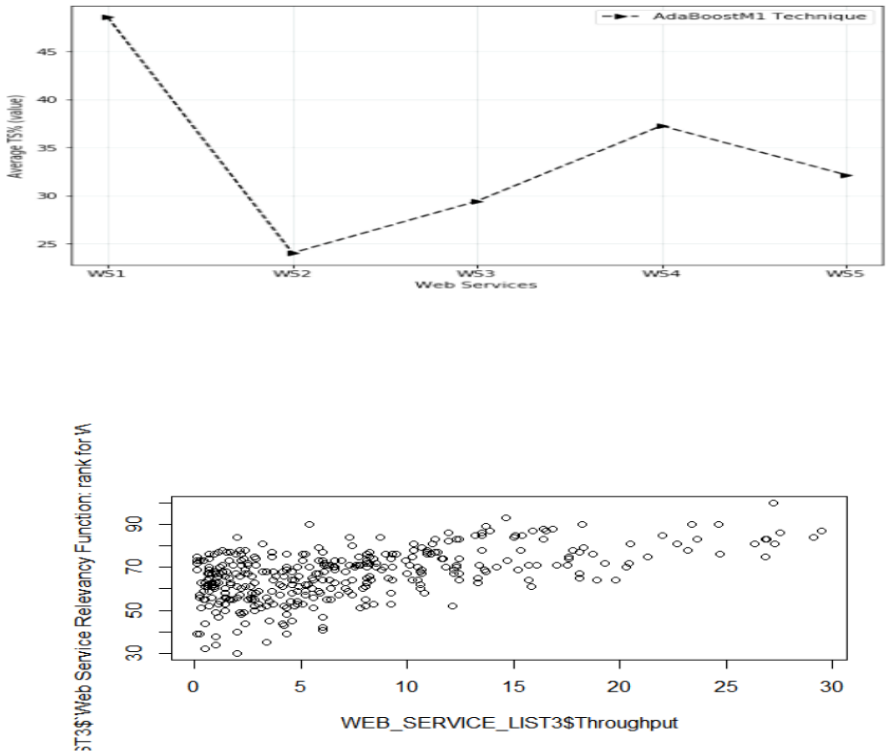

Figure: 5.1 Service Performance Statistics

Similarly, compute the Performance of Service (PS) factor for each service utilizing the binary classification illustrated in Fig: 5.1. Employing the same model, the values for the remaining web services, namely 3, 4, and 5, are also computed and interpreted, with the results plotted against each service. The calculation of the PS value involves assessing the truthfulness of service within the dataset, considering different values of a service with True Positives (T.P), False Positives (F.P), True Negatives (T.N), and False Negatives (F.N). All services are evaluated in terms of performance, taking into account various factors collectively and expressed through a relevance function, as depicted in the second figure above.

VI. CONCLUSION AND FUTURE ENHANCEMENT.

Enhancing service quality prediction in a distributed computing application environment poses numerous challenges, addressed through advanced application optimization mechanisms. The objective is to identify the best service within a composition of functionally similar services but with varying nonfunctional attributes. The performance of a service is evaluated based on user feedback, specifically focusing on throughput and response time. A fuzzy rule-based criteria, considering conditions like user feedback, is employed to achieve more accurate service performance prediction. This predictive modeling is particularly structured and effective within the n-tier application framework.

In the process of building models, realistic models capable of effective capacity planning are developed. These models, along with additional information, contribute to improved resource planning for diverse workloads, ultimately optimizing service delivery. To train classifiers on web services datasets, binary classification is implemented. The AdaBoostM1 classifier, selected for its boosting algorithm and high accuracy, demonstrates noteworthy results. Evaluation outcomes, supported by a real-world Quality of Service (QoS) dataset of web services, are validated for accuracy using cross-validation methods. This comprehensive approach aims to enhance the Performance of Service (PS) through improved predictive modeling and classifier training.

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