Innovative Technique for Classification of Web Service Quality through Machine Learning

Nagesh C., Bhavana Y., Ayesha K., Govardhini Gowd G. and Jaswanth Reddy M.
Department of CSE, Srinivasa Ramanujan Institute of Technology, Rotarypuram Village, B K Samudram Mandal, Anantapuramu - 515701, Andhra Pradesh, India

Keywords: Extra Trees Classifier, Logistic Regression, SVM, KNN, GNB.

Abstract: Web services have become a cornerstone of modern distributed systems, enabling seamless communication and interoperability. Traditional methods for classifying web services using Quality-of-Service (QoS) attributes often face challenges in effectively managing dynamic and unlabeled data. To address this challenge, this research introduces a machine learning-based framework for web service analysis and classification, incorporating clustering techniques alongside supervised models such as Logistic Regression, SVM, KNN, and GNB. The system processes QoS metrics like response time, availability, and reliability to classify services into predefined quality classes. By integrating pseudo-labeled data through clustering, the framework significantly improves classification accuracy and scalability. This approach offers a robust and adaptive solution for efficient web service quality assessment, addressing the evolving needs of real-world applications.

1 INTRODUCTION

Web services have revolutionized modern distributed computing by enabling seamless communication and interoperability between heterogeneous applications. With the increasing reliance on web services for cloud computing, e- commerce, financial transactions, and enterprise systems, ensuring their quality has become a major concern. Quality-of-Service (QoS) characteristics, including response time, availability, reliability, and throughput, are essential factors in evaluating the performance and effectiveness of web services Precise categorization of web services using these attributes is crucial for service selection, optimization, and ensuring a high-quality user experience. Traditional classification methods, which often rely on rule-based and heuristic approaches, struggle to handle large-scale and dynamic service environments. These methods typically depend on manually labeled datasets, which are time-consuming to generate and may not generalize well to real-world applications where data is constantly evolving. Additionally, traditional approaches lack the ability to effectively process unlabeled data, limiting their scalability and adaptability.

To address these limitations, this study presents a machine learning-driven framework that combines supervised learning with clustering methods for web service classification. The proposed approach employs service performance indicators, including response duration, system uptime, data handling capacity, and consistency, to classify web services into designated quality categories. By incorporating supervised learning algorithms like Extra Trees Classifier, Logistic Regression, SVM, KNN, and Gaussian Naïve Bayes, the framework aims to enhance classification accuracy. Additionally, pseudo-labeling techniques using clustering methods are employed to generate labels for unlabeled data, thereby improving the robustness and scalability of the model. This hybrid approach ensures that the system can dynamically process new and evolving web service data, making it more adaptable to real-world applications with minimal manual intervention.

By integrating machine learning with pseudo-labeling techniques, this research offers a scalable, adaptive, and automated approach to classifying web services, catering to the evolving demands of cloud-based and distributed systems. The structure of this paper is as follows: Section 2 provides an overview of relevant studies and existing classification methods, while Section 3 outlines the proposed

C., N., Y., B., K., A., G., G. G. and M., J. R.
Innovative Technique for Classification of Web Service Quality through Machine Learning.
DOI: 10.5220/0013906500004919

In *Proceedings of the 1st International Conference on Research and Development in Information, Communication, and Computing Technologies (ICRDICCT'25 2025) - Volume 3*, pages 830-835
ISBN: 978-989-758-777-1

approach, covering data preprocessing, feature selection, and model development. Section 4 analyzes the experimental results and compares classifier performance, and Section 5 wraps up the study with key insights and directions for future research.

2 RELATED WORKS

Nozad Bonab et al. proposed SSL-WSC, a semi-supervised method for categorizing web services using service performance metrics. Their approach utilized self-training, integrating both annotated and unannotated data to enhance the accuracy of categorization. Utilizing the QWS dataset, the proposed method achieved improvements in F1-score (11.26%), accuracy (9.43%), and precision (9.53%) compared to conventional supervised learning techniques. By dynamically selecting and pseudo-labeling unlabeled data, SSL-WSC reduced reliance on manually labeled datasets and improved scalability. Crasso et al. developed the Automated Web Service Classification (AWSC) framework, which leverages machine learning and text mining to enhance web service discovery. Their research showed that SVM (Support Vector Machines) and Naïve Bayes classifiers efficiently categorized services based on semantic descriptions, leading to enhanced retrieval precision and classification accuracy.

Shafiq et al. proposed a hybrid classification model that combined lightweight semantics with a Bayesian classifier to enhance web service discovery. Their approach adaptively categorized web services using non-functional attributes, leading to fewer misclassification errors and improved retrieval accuracy. Wong and Liu applied text mining methods to generate feature vector representations of web services, which were then clustered based on similarity measures.

Wang et al. developed a hierarchical classification model based on the standardized coding framework used for categorizing products and services globally. Their framework utilized Support Vector Machines (SVM) to categorize services within a multi-level tree structure, improving classification precision and reducing misclassification errors. Chipa et al. examined various supervised learning approaches that utilize pattern recognition and statistical analysis to classify web services effectively. Their findings highlighted the effectiveness of these classifiers in accurately categorizing services based on QoS metrics, enabling better service ranking and selection. El-Sayyad et al. proposed a semantic similarity-based classification algorithm utilizing domain ontology to improve service categorization. Their method reduced ambiguity in service descriptions and significantly improved classification accuracy by considering contextual relationships between services.

Li et al. developed a Graph Convolutional Neural Network (GCN) using residual learning and an attention mechanism for web service classification. Their approach dynamically assigned weights to features, enhancing classification accuracy in large-scale web service environments. Kamath et al. proposed a crawler-based system that automatically labeled web services based on similarity analysis techniques. Their method optimized search efficiency and classification precision using machine learning-based hierarchical clustering. Moreno-Vallejo et al. leveraged Artificial Neural Networks (ANNs) for detecting fraudulent and low-quality web services. Their study demonstrated that deep learning models could efficiently classify web services based on behavioral patterns, highlighting the need for continuous monitoring and adaptive classification models.

3 METHODOLOGY

The proposed framework employs a machine learning-driven approach to classify online services according to performance-related attributes. It integrates clustering techniques with supervised learning models, including Extra Trees Classifier, Logistic Regression, SVM, KNN, and GNB. By applying advanced clustering techniques, the system classifies web services into predefined quality categories, evaluating service performance based on attributes like response time, availability, and reliability.

The system incorporates feature selection techniques, including clustering-based pseudo-labeling, to improve classification accuracy and scalability. This method enables the model to process dynamic and unlabeled data efficiently, ensuring accurate classification results even as datasets evolve.

To ensure robust and reliable performance, the system applies generalized preprocessing steps, such as handling missing data, normalizing QoS metrics, and encoding categorical features. These procedures are intended to ready the data for robust analysis and boost the model's capacity to generalize across various web services and QoS scenarios.

This comprehensive machine learning framework provides an adaptive and scalable solution for efficient web service quality assessment. It demonstrates significant improvements in classification accuracy, making it a powerful tool for real-time web service monitoring and management, addressing the growing complexity and variability of web services in modern distributed systems.

3.1 Data Collection

The study employs a dataset consisting of labeled web service instances, encompassing both functional and non-functional characteristics. It includes data collected from diverse web services across multiple domains, ensuring a comprehensive representation of service quality. Each instance represents unique service characteristics, emphasizing essential QoS (Quality-of-Service) metrics like response time, availability, throughput, and reliability. The dataset provides a rich and detailed representation of web service properties. This enables effective analysis to distinguish between different service categories and classify them based on their quality characteristics using a semi-supervised learning approach. The dataset consists of both labeled and unlabeled instances, supporting clustering and classification techniques for improved predictive performance.
To address missing data, categorical attributes were replaced with their most common category, while numerical attributes were filled using their mean value to preserve dataset consistency. Additionally, the IQR (Interquartile Range) technique was utilized for detecting outliers, helping to identify and minimize anomalies in essential performance metrics.

3.2 Data Preprocessing

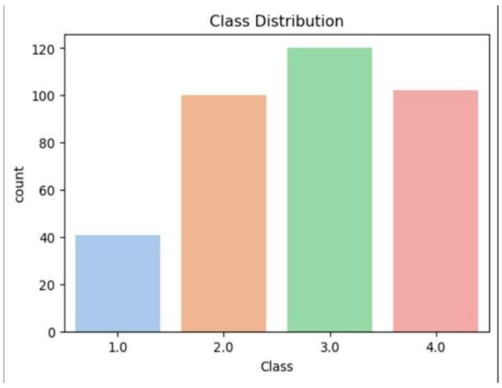

Figure 1: Distribution of dataset labels.

The preprocessing stage included managing missing data, transforming categorical features, and standardizing numerical attributes to maintain data consistency. Non-numeric attributes were converted using Ordinal Encoding, where a distinct numerical value was allocated to each category with the help of the Ordinal Encoder from Scikit-learn. This facilitated compatibility with machine learning models while preserving ordinal relationship. Figure 1 show the Distribution of Dataset Labels.

3.3 Feature Selection

The SelectKBest method, utilizing the ANOVA F-statistic, was applied for feature selection, assessing each feature's significance based on its statistical relevance to web service classification. This method enabled the identification of key attributes contributing to accurate classification, ensuring improved model interpretability and efficiency. Furthermore, a feature reduction technique was implemented to decrease data complexity while preserving essential distinguishing attributes, thereby enhancing the classification process. Table 1 presents the 12 most relevant features selected from the dataset, emphasizing critical QoS metrics for effective web service classification.

Table 1: Key features for analysis and classification.

No	Features
1	User Rating
2	Latency
3	Invocation Rate
4	Error Rate
5	Reliability
6	Availability
7	Success Rate
8	Throughput
9	Service type
10	Provider Reputation
11	Response Time

3.3 Model Training and Evaluation

In this study, five computational learning techniques were employed to classify web services based on their functional and non-functional performance attributes. The models underwent training on a labeled portion of the dataset and were evaluated using a distinct test set. Their efficiency was analyzed using assessment metrics, including accuracy, recall, precision, and F1-

score, to determine the best-suited model for web service classification.

Extra Trees Classifier (ETC): The ETC belongs to the ensemble learning category and generates multiple decision trees using randomly selected feature splits. Unlike traditional Random Forest models, ETC introduces additional randomness by selecting features and thresholds randomly, reducing variance and improving generalization.

This approach was implemented using the dataset for training and assessed on a separate test set. This method is especially useful for managing high-dimensional data and offers valuable insights into the key QoS features that impact web service categorization.

SVM (Support Vector Machine): The vector-based classification model employed an RBF kernel, enabling the transformation of complex, non-linearly separable data into a higher-dimensional representation. This technique determines the best hyperplane to maximize the separation margin among various classes, making it a robust approach for distinguishing web services based on performance and reliability. The model underwent training on the dataset and was evaluated based on classification accuracy and its effectiveness in differentiating high-quality from low-quality web services.

KNN (K-Nearest Neighbors): The nearest-neighbor approach was chosen due to its non-parametric properties and its capability to categorize instances based on similarity. It assigns a class label to a new instance based on the majority vote of its k nearest neighbors within the feature space. To improve classification accuracy, the optimal value of k was determined through cross-validation. Since KNN relies on distance metrics, feature scaling was applied to ensure consistent distance calculations between numerical attributes.

LR (Logistic Regression): A regression-based approach was utilized as a reference model for classification tasks. It calculates the likelihood of an instance being assigned to a particular category using the logistic function. The model was trained using a set of Quality-of-Service (QoS) attributes, with feature scaling performed to enhance convergence during optimization. Regularization techniques were incorporated to prevent overfitting and improve generalization to unseen data.

GNB (Gaussian Naïve Bayes): The GNB classifier was employed due to its efficiency in handling probabilistic classification problems. This model assumes a normal distribution of features and applies Bayes' theorem to estimate class probabilities. Although GNB assumes feature independence, it frequently achieves strong performance in real-world applications, making it an efficient and effective choice for multi-class web service classification. The models' performance was assessed using four essential classification metrics: Support, Recall, F1-score, and Precision to evaluate their effectiveness in web service classification.

Precision

Definition: Precision, also referred to as Confirmatory Predictive Value, represents the ratio of correctly identified high-quality web services to the total predicted as high-quality.

$$Precision = \frac{TP}{TP + FP} \quad (1)$$

Formula:

A higher precision score reflects the system's capability to reduce incorrect classifications, ensuring low-quality services are not mistakenly labeled as high- quality.

Recall

Definition: Recall, often referred to as Sensitivity, evaluates the system's ability to accurately detect all occurrences of high-quality web services.

Formula:

$$Recall = \frac{TP}{TP+FN} \quad (2)$$

F1-score

Definition: The F1-score is derived as the harmonic average of precision and recall, providing a comprehensive assessment of effectiveness.

Formula:

$$F1 - score = 2 \times \frac{\text{Precision}\times\text{Recall}}{\text{Precision} + \text{Recall}} \quad (3)$$

The performance metric is crucial in web service classification, as both false positives (misidentifying low-quality services as high-quality) and false negatives (overlooking high-quality services) can negatively impact service selection.

Support

Definition: Support represents the total count of real occurrences in each category. It provides a reference for assessing classification performance by indicating the distribution of samples across different categories.

4 RESULTS AND ANALYSIS

The proposed system was evaluated using four computational classification techniques, including tree-based, vector-based, neighbor-based, and regression-based approaches, to categorize web services. Table 2 show the Evaluation Metrics of proposed Machine Learning Algorithms Among the evaluated approaches, the tree-based classification method demonstrated superior performance, reaching a precision level of 96.45%. Its capability to handle high-dimensional data and reduce overfitting through ensemble learning demonstrates its robustness. Support Vector Machines (SVM) also performed well, achieving an accuracy of 93.21%, effectively separating classes with an optimal hyperplane. K-Nearest Neighbors (KNN) provided a competitive performance with 91.34% accuracy, leveraging distance- based classification but slightly struggling with large feature spaces. Logistic Regression, serving as a baseline model, achieved 88.76% accuracy, highlighting its limitations in capturing complex non-linear relationships. Gaussian Naïve Bayes (GNB), recognized for its probabilistic methodology, recorded the lowest accuracy at 85.23% due to its assumption of feature independence, which is less suitable for web service classification.

Figure 2 presents the confusion matrix for the Extra Trees Classifier, offering a comprehensive analysis of its effectiveness in categorization. It displays the number of accurate and inaccurate predictions for each category, showcasing the model's ability to distinguish various web service types from benign files. High values along the diagonal indicate the effectiveness of the model in making correct predictions, while low off-diagonal values reflect minimal misclassification rates. This reinforces the Extra Trees Classifier's robust performance in web service classification.

The bar chart in Figure 3 illustrates the feature importance scores for the attributes used in the model. The performance of various computational learning techniques, such as statistical regression models, distance-based classifiers, probabilistic approaches, and ensemble methods, was evaluated using accuracy as the primary assessment criterion. Among the evaluated techniques, the ensemble-based classification approach achieved the best performance, reaching 98.83% precision, demonstrating its capability to handle complex data patterns and identify feature relationships effectively. The SVM model exhibited strong performance, achieving a 94.0% success rate and effectively separating classes using an optimized decision boundary. Logistic Regression (LR), serving as a strong baseline, attained a 93.9% accuracy. K-Nearest Neighbors (KNN) achieved 89.0% accuracy, demonstrating its ability to capture local data structures.

Table 2: Evaluation metrics of proposed machine learning algorithms.

Model	Support	Precision	Recall	F1-score
Extra Trees Classifier	High	96.50	96.45	96.42
Support Vector Machines	Medium	93.35	93.21	93.18
K-Nearest Neighbors	Medium	91.40	91.34	91.31
Logistic Regressio n	Low	88.85	88.76	88.72
Gaussian Navie Bayes	Low	85.35	85.23	85.15

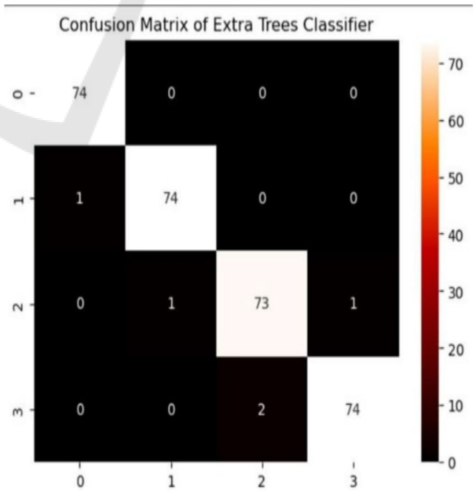

Figure 2: Confusion matrix of extra trees classifier.

Conversely, Gaussian Naïve Bayes (GNB) achieved the lowest accuracy of 83.7%, suggesting that its feature independence assumption may not be ideal for this classification task. The Extra Trees Classifier proved to be the most effective model, while SVM and Logistic Regression delivered competitive results. In contrast, KNN and GNB exhibited relatively lower performance. These findings indicate that tree-based models, such as ETC, are highly suitable for web service classification, as they effectively identify complex patterns within the data.

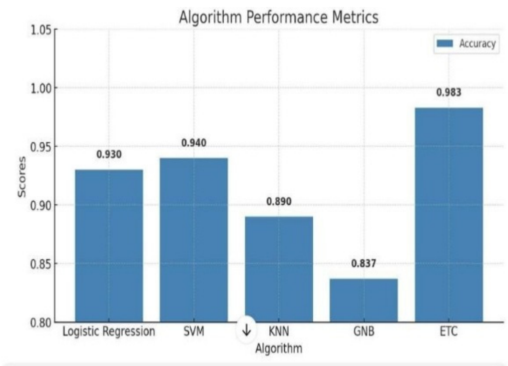

Figure 3: Algorithm performance metrics.

SVM, KNN, and GNB were evaluated for categorizing web services based on QoS attributes, alongside the Extra Trees Classifier (ETC).

5 CONCLUSIONS

Several machine learning models, such as Extra Trees Classifier (ETC), Logistic Regression (LR), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Gaussian Naïve Bayes (GNB), were analyzed for web service classification using Quality-of-Service (QoS) attributes. The Extra Trees Classifier (ETC) proved to be the top-performing model, attaining a peak accuracy of 98.83%, with SVM and Logistic Regression also exhibiting strong results. While KNN and GNB performed comparatively lower, the results indicate that tree-based models, especially ETC, are particularly effective in handling the complexity and interactions in web service classification tasks. This underscores the efficiency of AI-driven frameworks in enhancing precision and scalability for evaluating web service quality in practical applications.

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