Multi-Criteria Decision Analysis for Optimal Internet Service Provider Selection using Calibrated Random Forest

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***Abstract*—The Internet is integral to modern life, with internet service provider (ISP) offering appealing deals to meet the demand for unlimited data. However, reality often falls short of expectations. While recommendation systems exist, user-centric options are rare. This paper proposes a novel ISP selection methodology using user experience data and a calibrated random forest (CRF) model. Unlike traditional methods that focus on advertised features, this approach emphasizes user-defined criteria such as cost, device connectivity, and technical support experience. By analyzing survey data, the model highlights the critical link between user needs and support quality, enabling users to choose ISPs that prioritize customer service. The model demonstrates promising results with a strong R-squared value and low mean squared error (MSE). This user-centric approach fosters informed decision-making, potentially driving competition and encouraging ISPs to improve service standards, laying a foundation for future developments in ISP selection.**

***Index Terms*—Multi-criteria Decision Analysis, Calibrated Random Forest, User Experience, consumer-centric ISP selection, data-driven & personalized ISP recommendations**

I. Introduction

With the advent of digitalization, the internet has become a vital conduit that flows through almost every aspect of modern civilization [1]. Everyday lives are stitched together with the threads of dependable, fast internet access, whether it's for social media, entertainment, or remote work and education. But as people's need for connectivity increases, the market for broadband services has skyrocketed, and a plethora of internet service providers (ISPs) are fighting for customers' business [2].

Customers usually need suggestions determining which ISP delivers on its promises, especially regarding the critical technical support component. This difficulty can lead to dissatisfaction and potentially result in customers switching ISPs for better service. The struggle is about the reliability and effectiveness of customer support services that ISPs offer, which are crucial for maintaining customer loyalty and satisfaction, and determining which ISP delivers on its promises, especially regarding the vital technical support component [3]. This paper offers an innovative approach strategy that empowers customers in their search for the best ISP by utilizing user experience data and machine learning (ML). Unlike traditional approaches that mainly compare promised features, the suggested model of this study goes further.

Although various review platforms and recommendation systems exist for different services, there are few dedicated to ISPs. This study addresses this gap by introducing a novel framework using a calibrated random forest (CRF) model to analyze user survey data and explore relationships among factors like connected devices, internet speed needs, and cost. The model assesses the quality of technical support provided by ISPs, with data collected through a survey focused on user satisfaction metrics such as downtime, service usage duration, support quality, and the likelihood of recommending the ISP. The dataset is available on Mendeley Data [4]. This approach offers practical insights into improving ISP services by identifying providers that offer robust support aligned with users' unique needs, guiding them toward better choices.

The paper incorporates and examines the CRF model's performance, highlighting the effectiveness of multi-criteria decision analysis (MCDA) in generating personalized ISP recommendations. By integrating user experience data with ML, this research proposes an ensemble method using CRF to determine feature importance and assign weights for MCDA evaluation. The model shows promise in addressing user-centric service selection, offering a more tailored approach to ISP recommendations.

The following sections include related literature followed by the proposed methodology to outline the detailed implementation of the proposed model, and the results section presents an analysis of the model's performance followed by the concluding remarks.

II. Literature Review

The selection of any particular service is a complex decision-making process that involves multiple criteria, and

ISP selection is no exception as it includes service quality, cost, speed, and customer support. While there are numerous platforms and recommendation systems for various services, there seems to be a scarcity of dedicated ones for ISPs. This work aims to bridge this gap by taking a novel method. To ensure its success, an in-depth review of relevant literature is required. Recent advancements in ML and decision analysis methodologies have opened new avenues for enhancing this selection process. This literature review explores existing research in ML in recommendation systems, the application of ML techniques, particularly random forest and its calibrated versions for feature importance, and MCDA and decision support systems.

A. Machine learning in recommendation systems

This approach combines different recommendations and advanced algorithms, such as the k-nearest neighbor (KNN), to create a new era of personalized entertainment by fine-tuning suggestions to user preferences [5]. A strong focus on collaborative filtering, supported by various algorithms like clustering, support vector machines (SVM), deep learning (DL), and Bayesian methods, indicates an increasing interest in harnessing big data's potential to enhance recommendation quality and relevance [6], [7]. This exploration into MLs role within recommendation systems underlines their indispensable function in navigating the vast digital expanse. Its goal is to enhance content suggestions by thoroughly exploring established and new algorithms [8], [9].

Although ML has advanced, data scarcity and scalability have issues. A systematic review of machine-learning-based recommendation systems for e-learning addresses the challenge of navigating the vast array of online learning materials [10]. The crucial integration of AI into recommendation systems signifies a significant milestone, illustrating progression through the evolution, methodologies, and applications of these systems in a data-intensive online world [11]. Collectively, these insights indicate a transformative shift towards more refined, user-focused recommendation systems, spotlighting ML and artificial intelligence (AI) pivotal roles in shaping future directions and innovations.

Building on this, authors introduces a pioneering approach by considering the full spectrum of user preferences in [12]. This method promises enhanced match accuracy between users and content, suggesting future exploration of grouping algorithms to deepen personalization.

B. Random forest for feature importance

The practical benefits of random forest techniques are more than just theoretical [13]. They demonstrate their efficacy in developing more precise medical data classifiers by emphasizing the selection of informative features and showcasing their versatility. Addressing computational challenges introduces an efficient heuristic method that has proven especially useful in high-dimensional genomic data analysis by reducing computational load without compromising accuracy [14].

A comprehensive comparison of random forest selection methods aims to discern the most effective techniques for predictive modeling, indicating certain methods excel in prediction accuracy and computational efficiency [15], [16]. The significance of feature selection is further validated, demonstrating its critical role in enhancing ML model performance across various datasets, from banking to healthcare [17]–[20]. This reassures us about the importance of this step in our research.

At the frontier of this field, the innovative forest deep neural network (fDNN) classifier merges forest feature detection with DL, tackling gene expression data classification challenges [21]. This model's success in predicting outcomes underscores the potential of combining ML and feature selection.

C. MCDA and Decision Support Systems

The integration of multi-criteria decision making (MCDM) with problem structuring methods (PSMs) and ML has emerged as a compelling approach for tackling complex decision-making scenarios across various domains. This convergence has been particularly influential in areas such as environmental management and strategic planning, where the combination of cognitive maps with techniques like analytic hierarchy process (AHP) and technique for order of preference by similarity to ideal solution (TOPSIS) has facilitated more comprehensive and informed decision-making processes. The robustness of these integrated approaches is well-documented, highlighting their capacity to incorporate diverse perspectives and achieve nuanced outcomes [22].

In inventory management, a framework combining ML with MCDM techniques, particularly SVMs, has been successfully implemented within a major automotive company. This approach addresses inventory classification challenges and data imbalances, showcasing the potential of advanced analytics in real-world applications [23]. Digital recommendation systems also leverage MCDM, enhancing user experiences as they evolve from traditional models to hybrid and neural network-based systems [24]. Moreover, integrating MCDA with life cycle assessment (LCA) has redefined environmental impact assessments, combining stakeholder values with environmental data for more accurate insights [25].

In manufacturing, particularly sustainable practices, MCDM has driven greener and more informed decision-making [26]. Similarly, hybrid MCDM models with grey numbers have been utilized in evaluating the service quality of major airports in Spain, offering a new approach to complex service assessments [27]. In the energy sector, comparative studies of MCDM methods have supported crucial renewable energy decisions in Latvia [28]. Additionally, MCDM has been applied in urban walkability studies in Porto Alegre, influencing public perceptions and urban planning by prioritizing factors like safety and accessibility [29].

Furthermore, maritime service quality evaluation in India has adopted hybrid MCDM methods, enhancing service standards within the maritime industry [30]. A two-stage MCDM approach has been successfully implemented to improve bus service quality in Turkey, providing a practical framework for service enhancement [31]. Lastly, in the realm of cloud computing, MCDM-based service selection schemes have been crucial in navigating the abundance of services, extending their application to ISP and cloud service provider rankings, thereby facilitating systematic selection processes [32]–[34].

III. Methodology

This section presents the methodology for selecting the optimal ISP utilizing an MCDA approach integrated with a CRF model. The methodology incorporates user survey data, aiming to assess diverse ISPs grounded on user feedback. Fig. 1 represents the overview of the proposed methodology of this study.

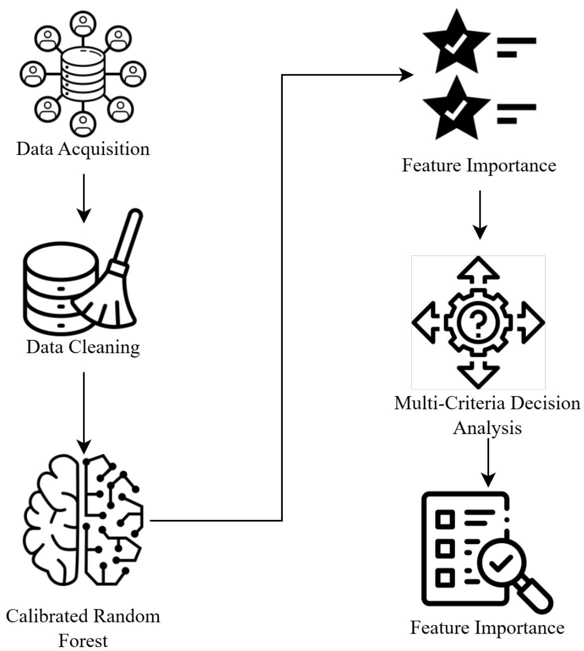

Fig. 1. Overview of the proposed methodology.

A. Data Acquisition

The methodology initiates with the acquisition of data via Google Forms distributed over the period of approximately 5 months across various online platforms. This approach ensured a diverse respondent pool while maintaining anonymity by not collecting personally identifiable data (PID). Responses were restricted to one per person to ensure data integrity.

The dataset comprises 812 responses. Among the respondents, 698, or 85.96%, are male, and 114, or 14.04%, are female. While the target was to collect data from all over the country, the majority of respondents are from the capital city, indicating a concentration of ISPs in that area.

Analysis shows that 67.4% of connections rely on optical fiber, highlighting a growing shift toward this technology. Dual-band routers, operating at 2.4 gigahertz (GHz) and 5 GHz, are preferred by 56.1% of users. Key satisfaction metrics include daily average downtime, service usage duration, technical support quality, and the likelihood of recommending the ISP, offering insights into user satisfaction and service perception.

B. Data Cleaning and Mapping

Categorical data, such as number of devices and user experience ratings, are transformed into numerical values employing predefined dictionaries. Missing values are rectified through imputation, employing the mean strategy for numerical features. ISP names are encoded using unique identifiers (e.g., $ISP1$, $ISP2$, etc.) to anonymize the data. Feature Selection: Relevant features that predict technical support quality are meticulously selected. These features encompass:

- **Number of devices:** Reflects the overall load on the internet connection.
- **Average downtime in minutes:** This signifies the frequency and duration of internet outages.
- **Cost in Bangladeshi Taka (BDT):** Portrays the affordability of the ISP plan.
- **Internet speed in megabits per second (Mbps):** Measures the data transfer rate of the internet connection.
- **How long have you been using this connection from your current ISP?:** Captures the user experience over time.

C. Model Building and Calibration

This subsection explains the model-building and calibration process for user-focused ISP recommendations. The CRF regression model was chosen for its strength in managing complex user data, avoiding overfitting, and providing clear insights into which factors matter most to users when evaluating technical support.

After building the model, MCDA is used to integrate these user priorities, considering multiple criteria like cost and reliability, not just speed. MCDA assigns weights to these criteria based on their importance to users. This combined approach uses user data and preferences to create personalized ISP recommendations.

1) Random Forest Regression: A CRF regressor is adopted as the ML model. This model is trained to prognosticate user ratings for technical support quality grounded on the selected features. Algorithm 1 outlines the workflow of the proposed model. Grid search cross-validation (GS CV) is deployed to fine-tune the $hyperparameters$ of the Random Forest model, ensuring its robust generalization to unseen data. MSE and R-squared metrics are computed to evaluate the model's proficiency in predicting user ratings. Actual user ratings are juxtaposed against predicted ratings to scrutinize the model's accuracy visually.

2) Multi-Criteria Decision Analysis: MCDA translates user experience data and feature importance into actionable recommendations. MCDA excels at providing decision-making insights when faced with multiple, often conflicting, criteria. In this study, MCDA utilizes the following factors extracted from the analysis:

Algorithm 1 ISP Rating Prediction Algorithm.

1: Load the dataset from a CSV file.
2: Handle missing values in the 'Placement' column.
3: Split the dataset into feature matrix (X) and target vector (y).
4: Encode categorical variables using Label Encoder.
5: Split the dataset into training and testing sets.
6: Initialize a $RandomForestRegressor$ model (rf) with $hyperparameters$:
    Number of estimators: $[100, 200, 300]$
    Maximum depth: $[None, 10, 20]$
    Minimum samples split: $[2, 5, 10]$
    Minimum samples leaf: $[1, 2, 4]$
7: Initialize a $GridSearchCV$ with rf model, parameter grid, 3-fold cross-validation, and scoring metric as negative mean squared error (MSE).
8: Train $GridSearchCV$ to find the best model.
9: Get the best $RandomForestRegressor$ model.
10: Extract feature importances from the $best\_rf$ model.
11: Normalize the feature importances.
12: Calculate the overall score for each ISP.
13: Get the top 5 ISPs based on scores.
14: Predict ratings for ISPs using the $best\_rf$ model.
15: Evaluate model performance using MSE and R-squared.

- **Feature Importance:** Feature importance is extracted from the trained random forest model, delineating the relative contribution of each feature in predicting technical support quality.
- **Weighting Criteria:** Fig. 2 shows that weights are allocated to each criterion (feature) based on importance. This reflects the significance of each factor when selecting an ISP.
- **Score Calculation:** The preprocessed data is harnessed to compute a score for each user predicated on the weighted summation of their experience across different criteria.
- **Top ISP Selection:** Users are subsequently ranked based on their calculated scores, with the top-ranked users (corresponding to the ISPs they use) identified as the most promising options predicated on user-defined criteria and their technical support experience.

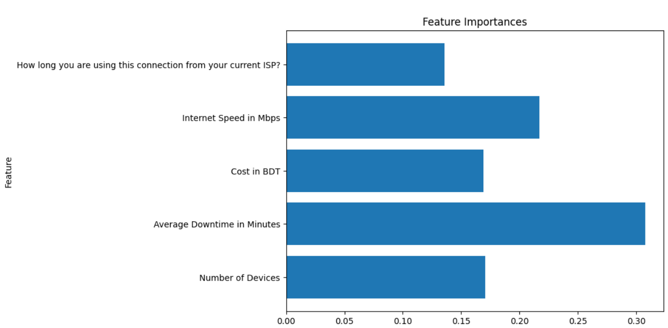

Fig. 2. Feature Importance for the ISP Selection.

Feature importance helps in understanding what users value most in ISP technical support. The top ISP recommendations guide users toward providers expected to offer better support, based on survey data. This data-driven approach combines user experience with ML to identify the best ISPs based on what users prioritize.

IV. Results and Discussion

The effectiveness of selecting an optimal ISP is crucial for ensuring a seamless online experience. In this section, first, the evaluation of the CRF model's performance in predicting user ratings for technical support quality is presented. Secondly, top ISPs are identified using MCDA, which incorporates the importance of features extracted from the trained Random Forest model. Through a comprehensive analysis, the aim is to elucidate the model's predictive capabilities and its implications for ISP selection.

A. Performance Evaluation

The CRF model demonstrated a MSE of 0.31 and an R-squared value of 0.74. The MSE value indicates that, on average, the model's predictions deviated by 0.31 units from the actual user ratings, which were measured on a scale of 1 to 5. The R-squared value suggests that the model can explain approximately 74% of the variance in the user ratings based on the selected features. These results highlight the model's ability to capture the relationship between user satisfaction and the chosen predictors, but there is still room for improvement in reducing prediction errors.

TABLE I
Model performance metrics

Criteria	Score
MSE	0.31
R-squared	0.74

These metrics in Table I indicate a moderate to good fit to the provided dataset. The MSE value suggests that, on average, the model's predictions deviated from actual user ratings by 0.31 units on a scale of 1 to 5. Additionally, the R-squared value of 0.74 implies that the model's selected features can explain approximately 74% of the variance in user ratings.

B. Model Interpretation

A visualization in Fig. 3 of actual versus predicted ratings reveals a generally positive correlation between the two, indicating the model's effectiveness in capturing trends in user ratings. However, the dispersion of data points around the trend line suggests that, although the model predicts user ratings with some accuracy, it does not perfectly match the actual ratings. This discrepancy might stem from factors not accounted for in the model or inherent variability in user satisfaction. These findings suggest that while the model is a valuable tool for predicting technical support quality, further refinements could improve its accuracy.

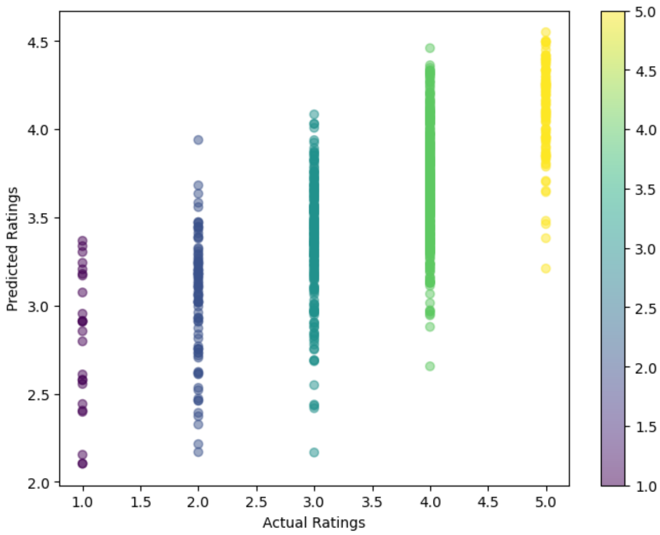

Fig. 3. Actual vs Predicted ratings.

C. Multi-Criteria Decision Analysis

Incorporating MCDA added significant value to the evaluation process by enabling a comprehensive assessment of ISPs based on multiple user-defined criteria. This method facilitated the identification of top-performing ISPs by consolidating diverse aspects of user experiences. The MCDA process involved assigning weights to each criterion, reflecting their relative importance in decision-making. These criteria encompassed a spectrum of factors crucial to user satisfaction, including the number of devices, average downtime, cost, internet speed, and overall satisfaction with the ISP's service quality.

Upon meticulous analysis, $ISP207$, $ISP29$, $ISP521$, $ISP196$, and $ISP548$ emerged as standout contenders, as presented in Table II. These ISPs demonstrated exceptional performance across the breadth of evaluated criteria, signifying their ability to consistently meet users' diverse needs and expectations. Their prominence underscores a commendable alignment with user-defined preferences and signifies their potential to offer a superior internet experience.

TABLE II
ISPs' PERFORMANCE SCORES

ISP	Score
ISP207	866.75
ISP29	853.66
ISP521	708.30
ISP196	704.21
ISP548	689.18

By applying MCDA, users can make informed decisions tailored to their priorities and preferences. This systematic approach ensures a holistic assessment of ISPs, empowering users to select providers that best align with their requirements and enhance their internet usage experience.

The results of this analysis indicate the potential of the CRF model in predicting user ratings for technical support quality and facilitating informed ISP selection through MCDA. While the model demonstrates a moderate-to-good fit to the dataset, there are limitations concerning data quality and generalizability. Nevertheless, identifying the top ISPs based on user-defined criteria provides valuable insights for users seeking optimal ISPs. Further refinement of the model and incorporation of additional user experience data could enhance its predictive capabilities and decision-making utility.

The MCDA approach, by assigning weights to factors such as the number of devices, average downtime, cost, internet speed, and satisfaction, allows for a nuanced ranking of ISPs. The top-performing ISPs, such as ISP207 and ISP29, were identified based on their overall scores across these criteria, demonstrating strong alignment with user preferences. This offers practical insights for consumers, helping them select ISPs that best meet their needs and potentially improving their satisfaction.

D. Implications of Results

The promising results from the CRF model and MCDA suggest that this user-centric approach can significantly improve the ISP selection process. By focusing on user-defined criteria rather than advertised features, this method empowers consumers to make more informed decisions. The implications of these findings extend beyond individual users, as the model can encourage ISPs to enhance their services, particularly in areas like technical support, to remain competitive.

V. Conclusion

This paper introduces a novel model using user experience data and ML to transform ISP selection. Unlike traditional methods that focus on advertised features, our approach emphasizes user-defined priorities, enabling consumers to choose ISPs that excel in critical aspects like technical support. The CRF model and MCDA offer personalized recommendations based on individual usage patterns and expectations.

This system benefits not only individual users but also the broader ISP market by highlighting user experiences and service quality, encouraging providers to enhance customer service. Future research could further enrich the model by incorporating data on internet speed reliability and user satisfaction, as well as refining MCDA weights through user preference surveys to improve accuracy and personalization.

Data and Code Availability

The codes and dataset used in this research are available at the following GitHub repository. Codes and Dataset GitHub Repository. The dataset is also available in Mendeley Data [4].

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