Analysis of Influencing Factors of Tourist Attractions Accessibility Based on Machine Learning Algorithm

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***Abstract*—Tourist attractions, defined by their cultural importance, aesthetic appeal, and recreational possibilities, are critical to the tourism industry. However, precisely evaluating tourism needs remains a difficult task, and research in this field is scarce. This research introduces an innovative remora-optimized adaptive XGBoost (RO-AXGBoost) model for predicting accessibility factors for tourist attractions. Data was obtained from Kaggle, and the suggested method was executed in Python. The RO-AXGBoost model's effectiveness was assessed utilizing metrics like Mean Absolute Percentage Error (MAPE) of 7.24, Mean Absolute Error (MAE) of 7.321, Root Mean Square Error (RMSE) of 10.241, and R-squared (R^2) of 85.7%. The results show that the RO-AXGBoost model surpasses conventional approaches by effectively discovering important determinants that have an important impact on the accessibility of tourist attractions.**

Keywords*—Tourist attractions; factors; tourism; remora optimized adaptive XGBoost (RO-AXGBoost)

I. Introduction

The intention to return is a vital component of tourism study, especially in the setting of urban tourism, where tourist loyalty is critical to economic development [1]. Comprehending the factors that impact tourists' choices to revisit attractions not only helps with consumer retention but also improves the efficacy of advertising tactics. With the advent of social media, tourists now have unprecedented accessibility to data, which greatly influences their travel decisions. Social media is an effective tool for influencing thoughts and experiences, establishing itself as an indispensable resource in the vacation decision-making procedure [2].

As social media platforms spread, the rise of social media influencers (SMIs) has altered how data is distributed [3]. These individuals, operating as independent advocates, can influence public opinion via a variety of digital channels, including tweets and blog posts. This dynamic shift in data access is especially important in the tourism industry, which is naturally vulnerable to external shocks like epidemics and catastrophes. The World Health Organization (WHO) has frequently suggested halting economic operations and public events during emergencies, demonstrating the industry's vulnerabilities.

Furthermore, environmental issues are posing new challenges to the modern tourism industry. As travelers become more conscious of the environmental effects of their operations, the need for "sustainable tourists"—those with smaller environmental impacts and more buying power—has increased [4]. The tourism industry is thus forced to adjust to these changing customer desires by incorporating environmentally friendly procedures.

Technological developments have become integral to the growth of the tourism industry, resulting in the idea of smart tourism [5]. This digital transformation not only improves tourism resource management but also provides stakeholders with timely access to pertinent data. The incorporation of sophisticated information technologies enables connection between tourism providers, thus improving the entire experience of visitors.

However, an important obstacle remains guaranteeing the safety and security of travel destinations. The growing issues of civil unrest, terrorism, catastrophic events, and health emergencies have increased the demand for dependable security evaluations [6]. Tackling these problems is essential to efficient travel planning.

In this setting, the purpose of this research is to improve the accuracy of predicting tourist attraction variables using an innovative remora-optimized adaptive XGBoost (RO-AXGBoost) model. This sophisticated machine learning method is expected to enhance predictive abilities in terms of important factors impacting tourist destinations. This study not only adds to the body of knowledge in tourism management but also provides decision-makers with useful information for tactical planning.

Additionally, to these advances in tourism management, current developments in image processing methods have substantially enhanced the excellence of visual content related to tourist attractions. Deep learning-based image improvement methods and the use of artificial intelligence algorithms have developed as methods for removing haze from images, leading to more obvious and appealing visuals. These improvements not only improve the visual appeal of tourist destinations, but they additionally perform an important role in impacting tourists' thoughts, eventually impacting their travel choices.

The accessibility of tourist attractions is critical to the achievement and enjoyment of tourism experiences. However, precisely predicting and evaluating the variables that impact accessibility is a difficult and underexplored problem. Conventional techniques frequently fall short of capturing the complex interplay of factors like transportation infrastructure, ecological sustainability, and tourist behaviour. The growth of smart technologies, as well as varying external conditions such as epidemics and climate change, have intricate the tourism sector even further. This study aims to close the gap by using sophisticated machine learning methods to present more precise, scalable, and flexible predictions of the variables that influence the accessibility of tourist attractions.

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This study intends to answer the following important questions:

1) What are the most crucial elements impacting the accessibility of tourist attractions?

2) How can machine learning techniques, especially the RO-AXGBoost model, be used to enhance the prediction accuracy of tourist destination accessibility?

3) How does the suggested RO-AXGBoost compare with other previous methods in terms of performance metrics like MAPE, MAE, RMSE, and R^2?

4) What potential knowledge can be derived from utilizing sophisticated predictive models for tourism management and planning?

The primary objectives of this study are:

1) To detect and evaluate the important determinants impacting the accessibility of tourist attractions.

2) To create and execute a new remora-optimized adaptive XGBoost (RO-AXGBoost) model that enhances the prediction accuracy of accessibility variables.

3) To compare the suggested method with previous machine learning techniques and assess its effectiveness utilizing metrics like MAPE, MAE, RMSE, and R^2.

4) To present knowledge and suggestions for tourism managers and urban planners on how to improve accessibility and sustainability in tourist destinations.

The paper's structure aims to direct the reader through the procedure of research, beginning with an introduction that presents background data on the significance of accessibility in tourism as well as technological advances that have allowed for more accurate prediction models in Section I. This is followed by a thorough literature review in Section II, which investigates previous research on machine learning methods in tourism and identifies gaps in current methodologies. The methodology in Section III describes the data sources, model creation, and performance assessment criteria, whereas the outcomes section summarizes the research's findings and compares the suggested RO-AXGBoost to previous techniques. The discussion in Section IV examines the results critically, emphasizing the study's novelty and implications. Finally, the paper summarizes the important contributions and proposes future research directions in Section V to build on the findings of this research.

II. Related Work

A study in [7] examined seasonal emotional shifts among travelers in natural forest environments using advanced methods such as Hrnet, SHAP, OSANetand, and XGBoost. Positive feelings were most common throughout three years, with varying distributions among seasons. The study contributed to the development of sustainable forest tourism by revealing subtle emotional reactions to landscape aspects.

Research in [8] used an IoT-enabled, deep learning-based DNN with a multi-class classification algorithm recommendation system to improve visitor experiences in smart cities. Personalized suggestions were informed by real-time data and feedback from travelers. Compared to previous models, our multi-label classifier performed better, attaining high accuracy and precision. Potential biases in the source data and the requirement for a substantial IoT infrastructure were examples of limitations.

Paper in [9] employed an improved STC-LSTM to forecast short-term vacation demand for travel. As compared to traditional approaches, the results show enhanced forecast accuracy. The limitations of the approach encompass dependence on certain data categories and possible problems with the model's regional generalization.

Research in [10] proposed a unique strategy centered on enhancing visitor experiences and reducing congestion to overcome the shortcomings of conventional T-RSs. Used deep reinforcement learning as opposed to just single areas of interest. Its effectiveness was evaluated against three baselines using Verona tourism data from 2014 to 2023. The heavy computing load and data requirements were among the drawbacks.

Research in study [11] proposed a three-stage methodology to anticipate tourism demand across numerous sites. It utilized multi-dimensional scaling to identify related attractions, mixed autoregressive models with LSTM networks to reflect spatial dependency and the scale of tourism and suggested a method for integrating predictors to increase prediction stability. The program performed exceptionally well in estimating the number of visitors to Beijing's 77 attractions, according to the results. Data accessibility and generalizability issues were two possible limitations.

The objective of the research [12] was to create a DNN model for predicting how well policies would function over time to lessen the effects of crises on the travel and tourism sector in developing nations. The model indicated that the most efficient and long-lasting strategy was to concentrate on both domestic tourist marketing and disaster preparedness, drawing on both past experiences and present difficulties. The intricacy of modeling dynamic systems and the availability of data were possible constraints.

A study in [13], which focused on incoming arrivals from Hong Kong, attempted to improve the accuracy of tourist volume predictions using deep learning techniques. The suggested SAE-Bi-GRU strategy beat benchmark models like PCA-Bi-GRU with the Baidu index and Google trends data. It was archived by using SAE for data dimension reduction and a Bi-GRU for model forecasting. The research's dependence on a single case study, however, presented a limitation.

Study [14] improved tourist analysis by combining deep-learning text categorization and spatial clustering approaches. Using Flickr data, it created nine tourist categories using topic modeling and LSTM classification. Spatial clustering determined the ROA for each category, indicating various elements impacting attraction. The technique provided extensive insights into visitor tastes and could be used outside tourism, although its dependence on Flickr data has limits.

The purpose of the study [15] was to better understand travelers’ binary emotional experiences at Dali tourist spots. SVM and LDA models were used, as well as geographic analysis. The results reflect a general trend of good attitude, with negative evaluations for select Dali city attractions. Service experience and pricing were revealed as important elements affecting travelers' attitudes. Limitations may include a dependence on internet evaluations and the study's location.

III. METHODOLOGY

In this section, the paper proposed a novel remora-optimized adaptive XGBoost (RO-AXGBoost) to forecast various factors associated with tourist attractions. We gathered data from Kaggle.

A. Data Collection

This paper gathers a dataset from Kaggle [16]; this dataset covers tourism attraction site data from 352 Chinese cities. Each city CSV file has 100 locations. The data comprises the location name, URL, address, site introduction, opening hours, image URL, rating, proposed visit duration, suggested season, ticket information, and tips.

B. Remora Optimized Adaptive XGBoost

The suggested technique, remora-optimized adaptive XGBoost (RO-AXGBoost), was selected for its capacity to manage intricate datasets and make precise predictions about accessibility elements of tourist attractions. This technique stands out because it incorporates optimization methods that improve the model's efficiency, rendering it especially appropriate for evaluating the variety of tourism data. This research's participants are a varied group of tourists with varying demographics like age, gender, nationality, and travel experience, guaranteeing a thorough comprehension of various viewpoints on accessibility. The study will make use of publicly available datasets, like those obtained from Kaggle, which include variables like travel frequency, desired attractions, accessibility issues, and socioeconomic status. This integration of sophisticated machine learning methods and large datasets intends to offer resilient knowledge of the factors that influence the usability of tourist attractions, eventually leading to better tourism management procedures.

RO-AXGBoost is a novel technique for anticipating several aspects associated with tourist attractions. It leverages the Remora Optimization technique to adjust XGboost parameters and operates at the best model optimization. By coordinating Remora's flexibility with XGBoost's robustness, RO-AXGBoost is a potent tool for tourist destination management and planning as it enhances the machine's accuracy and efficiency in predicting crucial measurable factors in the tourism sector industry. The integration of Remora's suppleness with the robustness of XGBoost is called RO-AXGBoost, which presents viable aid to key decision-makers within the tourism sector that can forecast the significant indicators necessary for strategic planning and management of destination tourism more effectively.

1) ROA: This section aims at introducing the new meta-heuristic that has been developed, known as the ROA. ROA is based on a symbiotic float trait that remoras use to cling to bigger living organisms like swordfish and whales to be in a better position to access food. Again, like all of the MAs, the ROA optimization technique's concept is derived from biological considerations. This one has incorporated some of the features from the WOA and the SCA, which is known for its efficiency in both the local and the global search. By selecting an integer variable called H (0 or 1), one can decide whether this strategy has to use a similar exploring manner to that in SCA or WOA. This flexible manner increases using search space in the case of ROA, but if compared to other approaches to refinement, this flexible manner decreases the level of accuracy in exploration.

a) Travel with free: Using an elite approach, the SFO strategy is employed by ROA to perform a global search in the swordfish algorithm. The Eq. (1) for updating positions can be stated as follows:

$$u_i(p+1) = X_{best}(p) - \left(rand \times \left(\frac{x_{best}(p)+x_{rand}(p)}{2}\right) - x_{rand}(p)\right) \quad (1)$$

In this instance $\boldsymbol{u_i(p+1)}$ represents a candidate position of the $i-th$ remora. At the present moment, the optimal position is$\boldsymbol{X_{best}\,(p)}$. An arbitrary remora location is denoted by$\boldsymbol{x_{rand}(p)}$. The letter$P$stands for the number of iterations that are currently in progress. And between 0 and 1, $rand$ is a random number. Additionally, depending on its experiences, remora may switch hosts. This situation allows for the creation of a new candidate position through:

$$u_i'(p+1) = u_i(p+1) + randn \times \left(u_i(t+1) - x_i(t)\right) \quad (2)$$

And the $i-th$ remora's candidate position is represented by $u_i'(p+1)$. The ith remora's prior location is denoted by $x_i(t)$. Additionally, a properly distributed random number is generated using $randn$.

b) Through fully eat: Remora may also attach themselves to humpback whales to feed. Therefore, remora will move similarly to humpback whales. The WOA method is used in ROA to do local searches. To be more exact, the bubble-net attacking approach employed in WOA is utilized. The changed position updating formulae are provided below:

$$u_i(p+1) = E \times f^S \times \cos(2\pi a) + x_{best}(p) \quad (3)$$

$$E = |X_{best}(p) - x_i(p)| \quad (4)$$

Here E is the separation between the food and the remora Eq. (4). Additionally, by employing the encircling prey mechanism in WOA, which is described as follows, the remora can generate a little step to further enhance the quality of the solution.

$$E' = u_i(p+1) - S \times x_{best}(p) \quad (5)$$

$$x_i(p+1) = v_i(p+1) + B \times E' \quad (6)$$

Here the newly created location of the $i-th$ remora is denoted by $u_i(p+1)$. In ROA, the remora factor, represented by the letter B, is set to 0.1. When using the aforementioned techniques, ROA outperforms well-known meta-heuristic algorithms like WOA, SFO, and HHO (see Eq. (5) and (6)).

2) Adaptive extreme Gradient Boosting (AXGBoost): In this study, we employ AXGBoost as the core method to forecast gains and handle high-dimensional assembly faults. Then, to get predictions that are even more accurate, we suggest adaptiveXGBoost.

$$\hat{o}_i = h_2(E_i) = \sum_{k_2=1}^{k_2} h_{k_2}(E_i), h_{k_2} \in \emptyset \quad (7)$$

Here $\phi = \{h(E) = \omega_{s(D)}\}$ is a grouping of decision trees. Each $tree\ h(E)$ corresponds to a structural parameter s and leaf weights ω, Eq. (7). The $i-th$analysis of tourist attractions is denoted by$\hat{o}_i$. The model is developed by minimizing the total loss function:

$$M = \sum_{i=1}^{N_t} m(\hat{o}_i, o_i) + \sum_{k_2=1}^{k_2} \Omega(h_{k_2}), \quad (8)$$

Here,

$$\Omega(h_{k_2}) = \gamma d + \varepsilon \|\omega\|^2 \quad (9)$$

$m(\hat{o}_i, o_i)$Refers to the loss function used to calculate the difference between the realistic and expected tourism attraction. dRepresents the number of decision tree leaves. The penalty period is represented by the symbol Ω, Eq. (8) and (9). The tuning parameters γ and ε regulate the complexity of decision trees. The square loss function was employed in this investigation.

$$\mathrm{m}(\hat{\mathrm{o}}_\mathrm{i}, \mathrm{o}_\mathrm{i}) = (\hat{\mathrm{o}}_\mathrm{i}, -\mathrm{o}_\mathrm{i})^2 \quad (10)$$

Iterative training is used for the loss function. For the $s-th$ repetition of the $i-th$ sample, we might write Eq. (8) as:

$$M^d = \sum_{i=1}^{N_t} m(\hat{o}_i^{(d-1)} + h_d(E_i), o_i) + \Omega(h_s) \quad (11)$$

XGBoost enhances the model by addingh_s, Eq. (10). The objective is optimized using a second-order approximation.

$$M^d \approx \sum_{i=1}^{N_t} \left[m(\hat{o}_i^{(t-1)}, o_i) + t_i h_i(E_i) + \frac{1}{2} p_i h_s^2(E_i) \right] + \Omega\ (h_s) \quad (12)$$

$$T_i = \varphi_{\hat{o}_i^{(t-1)}}\, m(\hat{o}_i^{(s-1)}, o_i) = 2 \times (\hat{o}_i^{(s-1)} - o_i), \quad (13)$$

$$G_i = \varphi_{\hat{o}_i^{(s-1)}}\ {}^2 m\left(\varphi_{\hat{o}_i^{(s-1)}}, o_i\right) = 2 \quad (14)$$

The first and second-order gradients are denoted as $T_i$and G_i. The equations are$m\left(\varphi_{\hat{o}_i^{(s-1)}}, o_i\right)$ Eq. (12)-(14).

An adaptive XGBoost model serves as the foundation for transfer learning, which uses parameter-based approaches. During the process of the transfer training phase, leaf weights from all trees in the adaptive XGBoost model are exchanged. It is constructed by training new trees and leaf weights. Fig. 1 illustrates the adaptive XGBoost framework.

$$\hat{o}_{2,i} = g_3(E_i) = \sum_{K_2=1}^{K_2} h_{k_2}(E_i) + \sum_{K_5=1}^{K_5} h_{k_2}(E_i), h_{k_2,} h_{k_5,} \quad (15)$$

The TF model predicts tourism for the $i-th$ sample, denoted as$\hat{o}_{2,i}$. $h_{k_{2,}}$Represents the trees in the enhanced XGBoost model, whereas $h_{k_{5,}}$is in Eq. (15). To increase the accuracy of tourism attraction predictions, the weights of leaves in $\boldsymbol{h}_{k_{2,}}$ are shared and newer leaf strengths in $\boldsymbol{h}_{k_{5,}}$are trained.

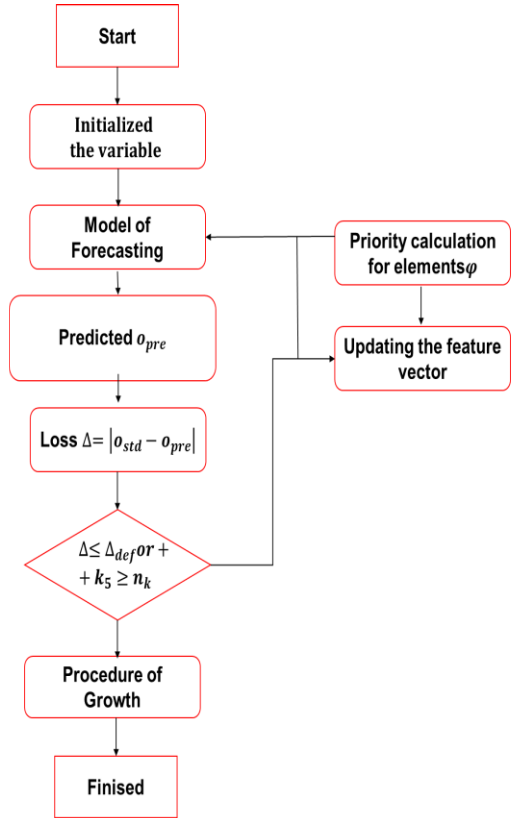

Fig. 1. Adaptive XGBoost.

3) Predicting RO-AXGBoost: The original technique that we used is called RO-AXGBoost, and it incorporates Remora Optimization, a newly developed meta-heuristic algorithm that refers to the behavior of remoras about sharks in improving the capabilities of XGBoost in predicting various aspects that are related to tourist attractions. Thus, our method of utilizing the Remora Optimization procedure to enhance the adaptiveness of XGBoost hyper-parameters enhances its quality in terms of its performance and capabilities of precisely predicting labeled tourism-related variables. These two components allow for better and more consistent forecasting, helping the entities in the tourism sector to optimize their decision-making process in terms of resource management, promotion, and visitors' handling, thereby contributing to the overall improvement of the visitors' experience and the sustainability of the destinations.

IV. Result and Discussion

Anaconda3 for Windows is utilized in this scenario on a PC powered by an NVIDIA GeForce RTX 3090 Ti GPU and 24GB of RAM. The hard drive capacity is 1TB, and the computer's processor is the Intel Core i7-8750H running at 2.20GHz. Python 3.10 is the main programming language, using TensorFlow 1.14.0 as a development framework. In the section evaluate the performance outcome for the proposed method. The proposed method is compared with existing methods and the performance is evaluated in different parameters such as MAPE, MAE, RMSE, and R^2. The existing methods are

BiLSTM [18], CNN-BiLSTM [18], MACBL [18], KNN [17], RF [17] and LR [17].

R^2 is an indicator of how accurately the variables that are independent predict the dependent variable. Fig. 2 illustrates on R^2 value. Compared to existing methods KNN (70.6), RF (74.9), and LR (76.5), our proposed method was superior (RO-AXGB 85.7). In comparison to existing methods, the suggested method RO-AXGB showed significant improvements in tourist attraction accessibility.

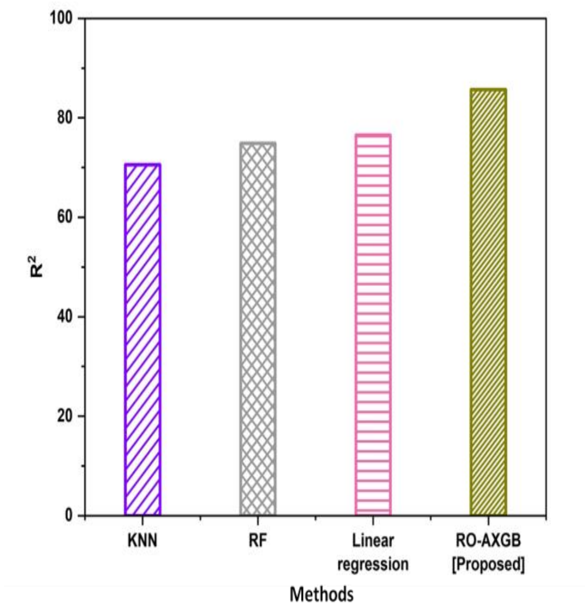

Fig. 2. Outcome of R^2.

The RMSE is the average of the squared discrepancies between anticipated and actual values. It indicates how much the model's predictions differ from the actual results, with lower values representing better performance. Fig. 3 illustrates the RMSE result. In comparison to the existing techniques BiLSTM (23.326), CNN-BiLSTM (16.354), and MACBL (13.837), our proposed is (RO-AXGB -10.241) lower than existing methods. It shows that our suggested method, RO-AXGB is effective for tourist attractions accessibility.

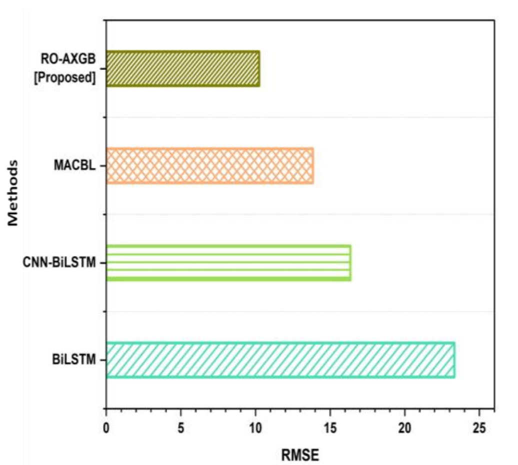

Fig. 3. Outcome of RMSE.

MAE estimates the average of the absolute differences between anticipated and actual values. It reveals information about the model's accuracy in forecasting, but it is less sensitive to extremes since it does not square the errors. Fig. 4 illustrates the MAE values. When compared to existing approaches BiLSTM (19.146), CNN-BiLSTM (11.354), and MACBL (8.928), our suggested technique is higher (RO-AXGB -7.321) than the existing method. It demonstrates that our suggested approach, RO-AXGB, successfully detects tourist attractions accessibility.

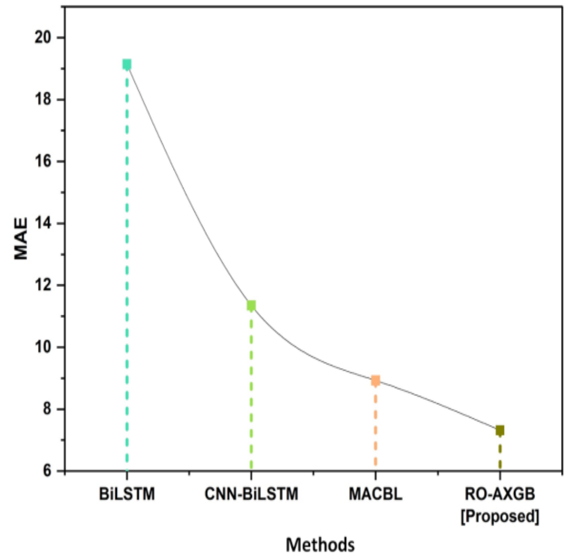

Fig. 4. Outcome of MAE.

MAPE is the average of the absolute percentage deviations between projected and actual values, represented as a percentage of actual values. Fig. 5 depicts the MAPE result and Table I illustrates the comparison of existing. When compared to the existing methods, BiLSTM (21.42), CNN-BiLSTM(16.96), and MACBL (10.21), our suggested method performs better (RO-AXGB -7.24). The successful demonstration of a tourist attraction's accessibility using the RO-AXGB approach indicates its effectiveness.

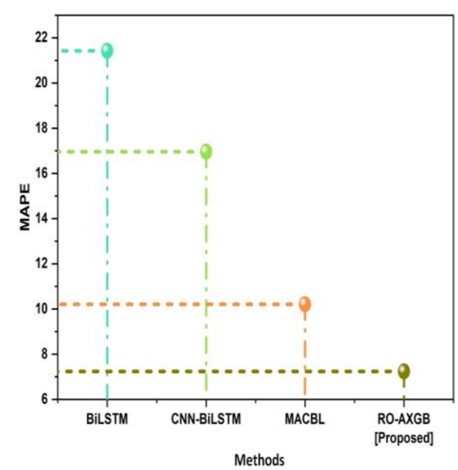

Fig. 5. Outcome of MAPE.

TABLE I. COMPARISON OF EXISTING METHODS WITH PROPOSED METHOD

Method	RMSE	MAE	MAPE	Method	R^2
BiLSTM	23.326	19.146	21.42	KNN	70.6
CNN-BiLSTM	16.354	11.354	16.96	RF	74.9
MACBL	13.837	8.928	10.21	LR	76.5
RO-AXGB	10.241	7.321	7.24	RO-AXGB	85.7

A. Discussion

Though the current methods of classifying influential factors of tourist attractions' accessibilities as BiLSTM, CNN-BiLSTM, MACBL, KNN, RF, and LR shed light on the circumstances of the objective, they all have their drawbacks. For that reason, both BiLSTM [18] and CNN-BiLSTM [18] models perform well in modeling sequential dependencies as well as spatial relations but can fail to adequately model long-range dependency and global context information. To address this issue, MACBL [18] employs a multiple-attentional mechanism in the feature extraction area to improve performance, but the additional attention mechanisms might increase the number of parameters for the resulting model and risk overfitting.

KNN [17], although the highlighted algorithm is easy to understand and implement, has its limitations regarding its scalability and effectiveness when applied to datasets containing high dimensions. RF [17] has high resistance to overfitting and nonlinearity but can have a low capacity for modeling high-level interactions among the variables. As a flexible, interpretable, and easy-to-implement method, LR [17] might not have the ability to capture the interactions and complex functional forms between the variables. Thus, although all of these methods yield valuable insights to analyze tourist attractions' accessibility, their flawed aspects point out to continued need for research and possibly a combination of all the methods to provide effective solutions regarding the various angles of the problem.

The drawback tackled, in this paper RO-AXGBoost provides an innovative approach for the interpretation of perturbing variables in the case of tourist attraction availability. Effectively applying the optimization techniques and the incorporation of adaptability to the equations make RO-AXGBoost highly efficient in capturing patterns of accessibility, which can aid in sound decision-making processes in the tourism sector. Its strength can be attributed to its capability to deal with big data, particularly concerning operating and learning in fluctuating environments and delivering solutions with noteworthy speed and accuracy.

This study's results show that the suggested remora-optimized adaptive XGBoost (RO-AXGBoost) technique outperforms previous methods in forecasting accessibility factors for tourist attractions. RO-AXGBoost outperformed other techniques (KNN, RF, and LR) in predicting accessibility-related variables, with an R^2 value of 85.7%. Additionally, the technique surpassed models like BiLSTM, CNN-BiLSTM, and MACBL in terms of MAE (7.321) and MAPE (7.24), demonstrating its superior accuracy in reducing prediction errors. However, in terms of RMSE, RO-AXGBoost produced a moderate outcome, indicating the necessity for future improvement in some situations. Compared to previous research that used BiLSTM and CNN-BiLSTM, which are efficient at capturing sequential data but have constrained long-range dependency managing, RO-AXGBoost's incorporation of optimization methods and adaptive learning proved useful in handling larger datasets and intricate interactions. This study presents a new combination of remora optimization and XGBoost, a method that not only improves efficiency but also tackles the constraints of previous models, resulting in more precise and effective predictions in tourism accessibility research.

To guarantee the resilience and validity of the suggested RO-AXGBoost method, cross-validation methods like k-fold cross-validation were used to decrease possible overfitting while also providing an accurate assessment of the model's generalization capacity. Furthermore, the suggested approach was compared to closely associated methods, like Gradient Boosting Machines (GBM) and XGBoost, which use boosting methods to enhance efficiency. While both GBM and XGBoost provide significant accuracy gains in intricate datasets, RO-AXGBoost incorporates adaptive optimization and feature weighting tactics, improving its capacity to handle high-dimensional data more efficiently. In comparison to XGBoost, which can struggle with particular dynamic trends, the RO-AXGBoost method handled accessibility-related perturbations more effectively because of its flexibility in handling various variables. Additionally, unlike GBM, which has higher computational expenses, RO-AXGBoost optimized execution speed, especially in environments demanding rapid decisions, rendering it ideal for tourism applications where quick accessibility knowledge are critical. The findings show that the RO-AXGBoost method improves both accuracy and speed, surpassing comparable techniques.

V. CONCLUSION

This research proposed an innovative remora-optimized adaptive XGBoost (RO-AXGBoost) technique for predicting important parameters influencing tourist attraction accessibility. The technique outperformed previous algorithms in prediction accuracy and precision, as measured by famous metrics like MAPE, MAE, RMSE, and R^2. Key factors impacting accessibility were successfully discovered, presenting useful information for tourism management and urban planning. However, while the technique produced impressive outcomes, some constraints must be acknowledged. The moderate RMSE values indicate possible fields for improvement, especially in dealing with variability and outliers in the data. Furthermore, while the study concentrated mainly on accessibility, further investigation into other dimensions of tourist satisfaction, like convenience and environmental sustainability, could offer a more extensive picture of the tourism industry's difficulties.

Future work could include incorporating real-time data to improve the model's flexibility in dynamic settings, as well as investigating more sophisticated optimization methods to further decrease prediction errors. Furthermore, integrating factors such as tourist desires, environmental concerns, and sustainability into the model would provide more detailed insights into tourism planning and management. Extending the model to include various kinds of attractions and geographies may also enhance its generalizability and applicability in wider tourism settings.

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