Intelligent Networks and Systems Society

Acceptance Letter

International Journal of Intelligent Engineering and Systems (IJIES)

March 5, 2025

Dear Mochamad Hariadi,

Manuscript Title: A KNN-Based Stacking for Tourism Destination Recommender System Based on User Demographic Data

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We are looking forward to your further contribution to our journal.

Kind regards

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Received: January 6, 2025. Revised: March 5, 2025.

International Journal of
Intelligent Engineering & Systems

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A KNN-Based Stacking for Tourism Destination Recommender System Based on User Demographic Data

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Abstract: The tourism destination recommendation system plays a crucial role in helping tourists find destinations that match their preferences. However, existing systems struggle with managing complex demographic data, leading to suboptimal prediction accuracy and reduced user satisfaction. To address this challenge, this study introduces a novel ensemble learning approach called KNN-Based Stacking, which enhances recommendation accuracy by effectively capturing diverse demographic patterns. Unlike conventional methods that rely on a single predictive model, the proposed approach integrates multiple KNN (k-Nearest Neighbors) variations with different neighborhood sizes ($k = 10$, $k = 15$, and $k = 20$) as base learners and optimizes prediction results using Logistic Regression as a meta-learner. This strategy allows the model to leverage the strengths of different KNN configurations, improving its ability to generalize across varied user profiles. Experiments were conducted on a dataset of 1,000 users with demographic attributes linked to 14 tourism destinations. The performance of the proposed KNN-Based Stacking model was compared against Naïve Bayes, CART (Classification and Regression Tree), SVM (Support Vector Machine), and Random Forest, demonstrating superior performance across all metrics. The model achieves 86.89% accuracy, 87.18% precision, 86.89% recall, and 86.93% F1-score, confirming its effectiveness in improving personalized tourism recommendations. This study contributes a novel ensemble learning strategy tailored for tourism recommendation systems, offering a more adaptive and accurate approach for handling complex user demographics. Future research can explore deep learning-based hybrid methods and real-time optimization techniques to further enhance recommendation performance.

Keywords: Tourism recommender System, KNN-based stacking, KNN, Logistic regression, Demographic data, Ensemble learning.

1. Introduction

Tourism recommendation systems play a crucial role in helping travelers find destinations that align with their preferences. However, existing models often struggle to handle the complexity of demographic variables, such as age, gender, occupation, marital status, and travel habits [1-4]. Traditional recommendation approaches, including CBF (Content-Based Filtering) and CF (Collaborative Filtering), have limitations in accommodating user heterogeneity [5]. These methods often fail to personalize recommendations effectively, leading to suboptimal accuracy and decreased user satisfaction.

Among various machine learning techniques, KNN is frequently utilized in recommendation systems due to its ability to measure the similarity between users based on preferences [6]. However, conventional KNN models face significant challenges in parameter selection and computational efficiency, making them less suitable for large-scale tourism applications [7].

Several studies have attempted to improve tourism recommendation systems using advanced machine learning techniques. Fahrizal et al. integrate Neural Networks with CF and CBF. This method shows that CF achieves higher precision than other approaches. However, CF still experiences obstacles such as cold start problems and dependence on data quality [8]. Shrestha et al. applied Gradient Boosting and Random Forest to improve the accuracy of the recommendation system. This method can improve the accuracy of recommendations but is still limited in handling real-time data. This study highlights the need for a more adaptive and accurate approach in tourism recommendation systems [9].

Arif et al. examined the MCRS (Multi-Criteria Recommender System) based on destination rating with eight assessment criteria. The system applies cosine-based similarity to measure similarities between players and previous traveler datasets. However, this system has weaknesses such as relatively low accuracy, which is 0.60. High dependence on rating data can affect the quality of the recommendations produced [10]. Meng et al. using CNN-BiLSTM (Convolutional Neural Network - Bidirectional Long Short-Term) for the classification of tourist review sentiment in IoT-based smart tourism. This method compares performance with BiLSTM (Bidirectional Long Short-Term Memory) and TextCNN (Text Convolutional Neural Network) and shows the best results in accuracy and F1-score. However, this method relies on the quality of review and rating data which can lead to bias in classification [11].

To address these challenges, this study introduces a novel KNN-Based Stacking approach that enhances both accuracy and adaptability in tourism recommendation systems. Unlike conventional KNN models, which suffer from sensitivity to parameter selection and computational inefficiency, the proposed approach combines multiple KNN variations (k=10, k=15, k=20) as base learners to capture diverse user preference patterns. Furthermore, Logistic Regression is employed as a meta-learner, enabling the model to make more robust predictions by dynamically optimizing the contribution of each base learner. This stacking-based ensemble method improves predictive accuracy while maintaining computational efficiency, making it highly suitable for tourism recommendation applications.

The proposed model offers several advantages over existing approaches. First, it achieves higher accuracy and personalization by integrating multiple KNN variations to better capture user preferences. Second, it reduces sensitivity to hyperparameter selection, addressing a key limitation of standalone KNN models. Third, the approach improves adaptability to demographic variations, providing more reliable recommendations across diverse user groups. Lastly, it demonstrates competitive performance compared to state-of-the-art machine learning methods, as shown by comparative analysis. The results confirm that KNN-Based Stacking significantly outperforms Naïve Bayes, CART, SVM, and Random Forest, leading to more precise and personalized tourism recommendations.

The contributions of this research are as follows:

1. Development of a KNN-Based Stacking model to improve the accuracy and reliability of tourism recommendation systems.
2. Comparative analysis with multiple baseline models (Naïve Bayes, CART, SVM, and Random Forest) to assess performance improvements.
3. Evaluation of the impact of demographic data on travel preferences, highlighting key attributes that influence destination selection.

The results of this study demonstrate that the KNN-Based Stacking model outperforms conventional methods, leading to enhanced recommendation accuracy and personalization. This improvement is expected to increase tourism engagement and support economic growth in the tourism sector. Furthermore, the approach presented in this study can be extended to other domains that rely on demographic data analysis, such as e-commerce, healthcare, and personalized marketing. Future research directions include the exploration of deep learning techniques and real-time recommendation optimizations to further enhance system performance.

2. Related work

Recommendation systems have seen widespread adoption across various industries, including entertainment, e-commerce, and tourism [12-14]. In recent years, research has explored the integration of demographic data to improve recommendation accuracy and mitigate challenges such as the cold start problem [2]. Tourism destination recommendation systems have traditionally relied on CF, CBF, and machine learning-based approaches [8, 12, 15]. However, despite significant advancements, existing models struggle to effectively leverage demographic data for personalized recommendations.

This section reviews related research in two key areas:

1. Demographic Data-Based Recommendation Systems - Examining how demographic features enhance recommendation accuracy.
2. Tourism Destination Recommendation Systems - Evaluating existing approaches and identifying gaps in their ability to personalize recommendations.

Additionally, this section highlights a research gap, serving as the foundation for the proposed KNN-Based Stacking approach in tourism recommendations.

2.1 Demographic data-based recommendation system

Several studies have demonstrated that incorporating demographic data enhances recommendation accuracy. Ananth et al. developed the IDMRS (Indian Demographic Movie Recommender System), which integrates age, gender, and occupation into its recommendation process, resulting in more personalized movie recommendations compared to traditional rating-based systems [3]. Odumuyiwa & Oloba showed that demographic-based CF improves accuracy when an entropy-based method is applied to the MovieLens dataset [2]. Additionally, Bobadilla et al. and Sharma et al. introduced DeepUnHide, a deep learning model that extracts hidden demographic patterns, enhancing feature selection and classification performance [1, 16].

Some studies have combined demographic data with other methods to improve the accuracy of recommendation systems. Qabbaah et al. applied K-Means Clustering to group users by age and gender before using the recommendation algorithm [17]. B.L. combines TBCF (Typicality-Based Collaborative Filtering) with demographic data to address cold start issues and improve to further improve the accuracy of recommendations [5].

Despite these advancements, most research has focused on entertainment and e-commerce domains, leaving demographic-based tourism recommendation systems largely unexplored. This presents an opportunity to develop more adaptive and accurate recommendation models tailored to tourism preferences.

2.2 Tourism destination recommendation system

The tourism destination recommendation system continues to evolve by utilizing various approaches based on machine learning and artificial intelligence [15, 18]. Arif et al. developed a MCRS based on destination ranking with eight assessment criteria. They applied cosine-based similarity techniques to measure similarities between users and previous travelers. The results showed that the number and composition of destination ratings affected the accuracy of the system, with an average accuracy of 0.60. Although this method is able to improve the accuracy of recommendations, the system still depends on the quality of the ranking data [10]. Another approach is carried out by Fahrizal et al., which combines CF and CBF with Neural Networks. Their model successfully reduced cold start problems and improved recommendation precision with RMSE (Root Mean Square Error) values below 0.37, although it still required a large dataset for effective training [8].

A machine learning-based approach is also applied for more personalized and accurate recommendations. Shrestha et al. developed a data-driven system that considers user demographics, behavior, and preferences. They use various machine learning models such as CART and Random Forest to improve the accuracy of predicting tourist destinations [9]. Meanwhile, Meng et al. applied the CNN-BiLSTM model to analyze the sentiment of tourist reviews in the smart tourism system. This model shows high performance with an accuracy of 85.1%, superior to BiLSTM and TextCNN models. Although effective in text analysis, this method does not directly provide travel recommendations but helps understand user sentiment [11]. In addition, another study combined FPGA (Field-Programmable Gate Array) and CNN (Convolutional Neural Network) to forecast travel demand, which showed improved accuracy over traditional statistical methods [19]. Although many advances have been made, most systems still face challenges in real-time adaptation and scalability, so future research needs to integrate more flexible and responsive methods.

2.3 Research gap

Despite advancements in tourism destination recommendation systems, several critical research gaps remain unaddressed. Most existing studies primarily rely on CF and CBF, yet fail to incorporate demographic data as a core factor in recommendation processes. However, research in entertainment and e-commerce domains has demonstrated that demographic attributes significantly enhance recommendation accuracy.

The lack of demographic-aware tourism recommendation models suggests an opportunity for improvement in this domain.

Additionally, studies that integrate machine learning techniques in tourism recommendation systems remain limited to basic models, such as

Received: January 6, 2025. Revised: March 5, 2025.

CART, Naïve Bayes, and Random Forest. While effective in certain contexts, these approaches often lack adaptability and struggle with complex user preference patterns. Stacking ensemble learning, a method proven to enhance predictive performance across various fields, has rarely been explored in tourism recommendation systems. Given its potential to combine multiple classifiers for more robust predictions, stacking offers a promising yet underutilized approach in this field.

Furthermore, although KNN is a widely used method in recommendation systems due to its ability to measure user similarity, it suffers from computational inefficiencies and sensitivity to parameter selection (*k*-value) when dealing with large datasets. Existing research has not yet explored the integration of KNN within a stacking ensemble framework for tourism destination recommendations.

This study aims to bridge these research gaps by developing a KNN-Based Stacking model, which integrates multiple KNN variations (k=10, k=15, k=20) as base learners and Logistic Regression as a meta-learner. By leveraging demographic data and stacking techniques, this approach is expected to:

1. Enhance the accuracy and adaptability of tourism destination recommendations.
2. Improve computational efficiency by combining multiple KNN models with a meta-learner.
3. Address the lack of demographic-aware ensemble learning approaches in tourism recommendations.

The results of this study contribute to the development of a more personalized, accurate, and scalable recommendation system. Future research can further extend this approach by exploring deep learning-based hybrid models and real-time recommendation optimizations to improve system performance.

3. Design and method

This section describes the architectural metrics, datasets, preprocessing, model design, and evaluation in this study. The proposed method aims to improve the accuracy of the tourism recommendation system by implementing KNN-Based Stacking. This model integrates KNN variations as base learners and Logistic Regression as meta learners in stacking ensemble learning. This approach optimizes the use of user demographic data to generate more accurate recommendations.

3.1 Recommendation system design

The system architecture consists of six main modules: data collection, preprocessing, feature selection, KNN-Based Stacking, prediction, and evaluation. The system is designed to improve the accuracy of tourism recommendations by implementing KNN-Based Stacking in an ensemble framework. Fig. 1 illustrates the architectural structure of the proposed system.

Fig. 1 shows that the KNN-Based Stacking recommendation system consists of several main stages. The first stage is data collection, which includes user demographic information, travel preferences, and destination characteristics. We then preprocess the data with cleaning, normalization, and handling of missing values to ensure data quality. After that, we perform a feature selection to determine the most relevant attributes in the recommendation model. The selected features are used in KNN-Based Stacking, which is the core of this recommendation system. This model combines several KNN with different numbers of neighbors (k=5, k=10, and k=15) as base learners. The system then integrates the KNN output using Logistic Regression as a meta-classifier to improve the accuracy of recommendations.

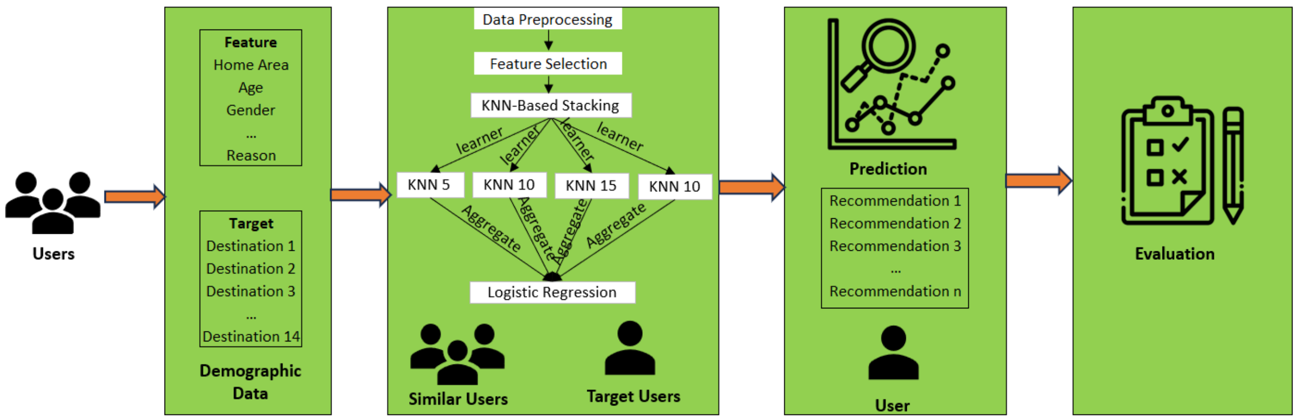

Figure. 1 Proposed system architecture

At the prediction stage, the system generates a list of tourism destinations based on the same user preferences. We compare the profiles of new users with other users who have similar characteristics. The final stage is the evaluation of the model, which measures accuracy, precision, recall, and F1-score. This evaluation ensures the effectiveness of the method in improving the quality of recommendations. The proposed system aims to produce more accurate recommendations. This approach allows the system to capture complex patterns in demographic data. With this method, the system can provide more personalized and relevant recommendations.

3.2 Data collection

This study collected datasets through questionnaires distributed to 1000 tourist respondents. This questionnaire is designed to obtain information about travel preferences based on the personal experiences of respondents. Each respondent gave a response related to the destinations they had visited and the reasons for choosing destinations. The data collected includes demographic information of travelers, such as home area, age, gender, hobbies, marital status, education, occupation, and travel frequency [19]. In data analysis, these attributes are grouped into feature attributes and target attributes. Feature attributes represent user characteristics, while target attributes indicate the preferences of tourist destinations. Table 1 displays the classification of feature attributes used in this study.

This study focuses on 14 tourism destinations in Batu City as the object of analysis in the recommendation system. Batu City has a variety of tourist destinations, including natural, cultural, and entertainment tourism. These fourteen destinations are used as target attributes in the recommendation model to reflect traveller preferences [19]. The target attribute data is arranged in tables to facilitate the analysis and modeling of the recommendation system. Table 2 details the 14 tourism destinations that are the focus of this study by considering the diversity of tourism types in Batu City.

Table 1. The feature attributes

No	Feature	Variable	Feature Values
1.	Home Area	X1	Rural, Suburban, Urban
2.	Age	X2	7-11, 12-25, 26-45, > 45
3.	Gender	X3	Female, Male
4.	Hobby	X4	Gaming, Hiking, Photography, Reading, Swimming, Travelling
5.	Marriage Status	X5	Married, Single
6.	Education	X6	College, Elementary School, High School
7.	Work	X7	Student, Civil Servant, Entrepreneurship, Private Employees
8.	Frequency of Travelling in Last Year	X8	Frequently (6-10 times), Never, Occasionally (3-5 times), Rarely (1-2 times), Very Frequently (>10 times)
9.	Types of Tourism Frequently Visited	X9	Adventure, Culinary, Cultural, Nature, Urban
10.	Reason for Travelling	X10	Business, Education, Family Visit, Health, Recreation, Others

Table 2. The target attributes

No	Tourism Destination	Item	Distributions	
			Recommended	Not Recommended
1.	Jatim Park 1	Y1	516	484
2.	Jatim Park 2	Y2	521	479
3.	Jatim Park 3	Y3	522	478
4.	Museum Angkut	Y4	502	498
5.	Selecta	Y5	514	486
6.	BNS	Y6	493	507
7.	Eco Green Park	Y7	448	552
8.	Alun-Alun Kota Batu	Y8	513	487
9.	Kusuma Agro	Y9	418	582
10.	Cangar	Y10	448	552
11.	Coban Talun	Y11	444	556
12.	Pemandian Songgoriti	Y12	437	563
13.	Coban Rais	Y13	398	602
14.	Predator Fun Park	Y14	370	630

This mapping allows the recommendation system to provide more personalized and relevant results. With this approach, the system can tailor recommendations based on user demographic data.

Target attribute data is arranged in the form of tables to facilitate analysis and modeling of the recommendation system. Table 2 specifically details the 14 tourism destinations that are the focus of this study, taking into account the diversity of tourism types available in Batu City. With this mapping, the recommendation system can generate more personalized and relevant recommendations for users based on their demographic data.

3.3 Data preprocessing

We convert categorical data to numerical format to make processing easier in machine learning. Label coding techniques are used to convert each category into a unique numerical value. This method assigns a sequence number based on predefined rules. This conversion helps standardize the data to be compatible with the predictive model [21]. We process the data that has been encoded to recognize patterns in traveler preferences. The recommendation model utilizes this data to improve the accuracy of tourism destination predictions.

Eq. (1) defines the label coding function used in the conversion process of categorical variables.

$$f(x) = i, \text{ where } x = x_i \quad (1)$$

Label encoding is used to convert categorical variables into numerical representations, ensuring compatibility with machine learning models. The function $f(x)$ assigns a unique numerical value i to each categorical variable x_i. The assigned values range from 0 to (c-1), where c represents the total number of unique categories.

3.4 Feature selection

The ANOVA (Analysis of Variance) method evaluates the significance of features in the feature selection process. The system uses ANOVA to measure the relationship between independent features and target variables. This technique compares the variability between groups with the variability within groups to determine the most influential features [23]. The model selects the features with the highest significance value to improve prediction accuracy. This process helps eliminate irrelevant features thereby improving the efficiency of the system. With this approach, machine learning models can optimize data utilization in predictive analytics. Eq. (2) states the calculation of the F-statistic value in the evaluation of feature selection using ANOVA.

$$F = \frac{MSB}{MSW} \quad (2)$$

MSB (Mean Square Between Groups) measures variability between groups and is calculated using the following formula:

$$M\dot{S}B = \frac{SSB}{k-1}$$

MSW (Mean Square Within Groups) calculates the variability within a group and is expressed by the following formula:

$$M\dot{S}W = \frac{SSW}{N-k}$$

SSB (Sum of Squares Between Groups) is calculated using the following formula:

$$SSB = \sum_{\iota=1}^{k} n_\iota (\bar{X}_\iota - \bar{X})^2$$

SSW (Sum of Squares Within Groups) is calculated using the following formula:

$$SSW = \sum_{\iota=1}^{k} \sum_{j=1}^{n_\iota} (X_{\iota j} - \bar{X}_\iota)^2$$

In the ANOVA calculation, there are several main parameters used to measure data variability. The k parameter indicates the number of groups in the analyzed dataset. The N value represents the total number of samples used in the study. Each group has ni which indicates the number of samples in the i-th group. The value of X_{ij} represents the value of the j-th sample in the i-th group, which is used to calculate the variability within the group. The system calculates as the average of the values in the i-th group, while $\bar{X}$ representing the overall average of all samples.

3.5 Stacking technique in ensemble

The stacking technique in ensemble learning combines predictions from several basic learner models to improve the accuracy of the system. Each basic learner generates an initial prediction, which is then used as input to the meta-model. Meta-models process and integrate these predictions to improve the accuracy and generalization of the model. This approach allows the system to capture patterns that are invisible to individual models. This process provides a significant advantage in a variety of machine learning applications [21, 24-26].

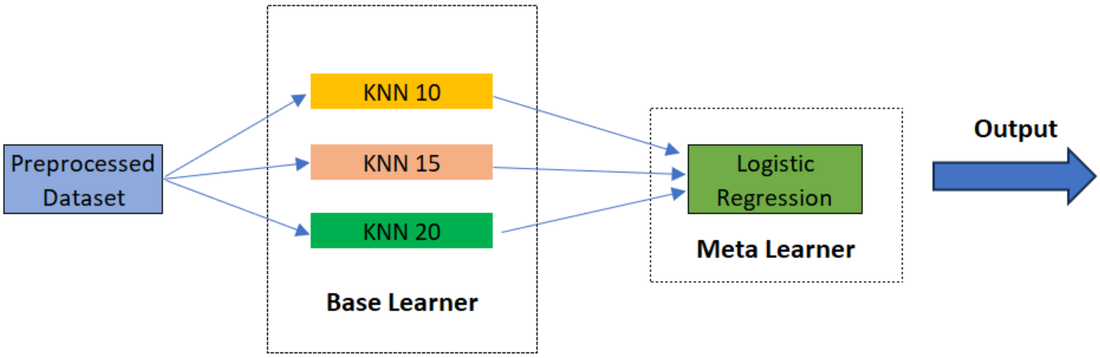

Figure. 2 The KNN-based stacking mode

This study uses logistic regression as a meta-learner because of its ability to process data effectively [27]. With this method, the system can generate recommendations that are more accurate and adaptive to user preference patterns.

Fig. 2 illustrates the stacking process in ensemble learning. The processed dataset is used as input for the basic learner model. Three KNN models with different *k*-values (*k*=10, *k*=15, and *k*=20) generate initial predictions based on patterns in the data. The system combines these predictions and uses them as inputs for meta-learners. Logistic regression as a meta-learner processes these predictions to produce a more accurate final output.

3.6 Inspection, splitting and validation

We used K-Fold Cross Validation to divide the dataset into subsets in model evaluation. Each subset alternately serves as test data, while the other subsets are used for model training. This process is repeated until all subsets are used as test data, and then the final result is calculated from the average performance score. This validation allows for objective evaluation of the model and helps reduce the risk of overfitting. This technique ensures that each data point is used as test data at least once [28]. We chose K-Fold Cross Validation because of its flexibility in dividing datasets equally. With this method, the system gets a more reliable and accurate evaluation in assessing the performance of the recommendation model.

K-Fold Cross Validation Algorithm:

1. Input:
   - Dataset *D* with n instance.
   - Number of folds *K* (set to 10).
   - Model *M* to be trained.
2. Steps:
   1) Shuffle the data in dataset *D*.
   2) Divide dataset *D* into *K* subsets (folds) of aproximately equal size:
      $D_1, D_2, \ldots, D_K$
   3) For each *K* :
      - Use fold D_k as the testing data.
      - Use the remaining folds ($D \setminus D_k$) as the training data.
      - Train model *M* on the training data.
      - Evaluate model *M* on the testing data.
      - Calculate the average of the evaluation metric recorded in each iteration.
3. Output:
   - The average evaluation metric of model *M* across *K* folds.
   - If needed, save the best-performing model based on its performance.

3.7 Confusion matrix and evaluation metrics

We evaluate the model's performance using a confusion matrix to calculate evaluation metrics. Accuracy measures the proportion of correct predictions to the overall test data. Precision evaluates the accuracy of the model in identifying positive classes based on the number of correct predictions. Recall measures the sensitivity of the model in correctly detecting positive classes. The F1 score combines precision and recall to assess the balance of the model's performance. This metric provides a comprehensive evaluation of the system's prediction effectiveness [29]. With this approach, research can improve the accuracy and generalization of recommendation models.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

$$Precision = \frac{TP}{TP+FP} \quad (4)$$

Received: January 6, 2025. Revised: March 5, 2025.

$$Recall = \frac{TP}{TP+FN} \quad (5)$$

$$F1 - Score = \frac{2\times(Precision\times Recall)}{Precision+Recall} \quad (6)$$

Eq. (3) evaluates the model's accuracy by calculating the ratio of correctly predicted samples to the total number of samples. The formula incorporates TP (True Positive), representing correctly predicted positive instances, TN (True Negative) for correctly predicted negative instances, FP (False Positive) for incorrectly predicted positive instances, and FN (False Negative) for incorrectly predicted negative instances, ensuring a comprehensive performance assessment. Eq. (4) defines precision as the proportion of correctly predicted positive cases (TP) to the total predicted positives (TP + FP), reflecting the model's reliability in identifying relevant instances. Eq. (5) calculates recall by dividing TP by the total actual positives (TP + FN), measuring the model's ability to detect all relevant instances. Eq. (6) determines the F1-score, which balances precision and recall using their harmonic mean, providing a more holistic evaluation of classification performance. By incorporating FP and FN into the assessment, this approach ensures a fair and objective evaluation, allowing the model to deliver more accurate and reliable predictions across various classification tasks.

4. Results and discussion

This section presents the results of the research and analysis of the proposed recommendation system. There are three main subsections, namely demographic feature analysis, model performance evaluation, and comparison with related research. Demographic feature analysis evaluates user characteristics that affect the preferences of tourism destinations. Model performance evaluation measures the accuracy and reliability of the algorithm in providing recommendations. Comparison with related research highlights the advantages of the proposed approach over other methods. The results of this study provide insight into the performance of the system in producing more accurate recommendations. This approach helps to increase the relevance of recommendations according to travelers' preferences.

4.1 Demographic feature analysis

The Demographic Feature Analysis subsection explores the distribution of user data based on demographic characteristics. The system uses this analysis to understand patterns of travelers' preferences based on the user's background.

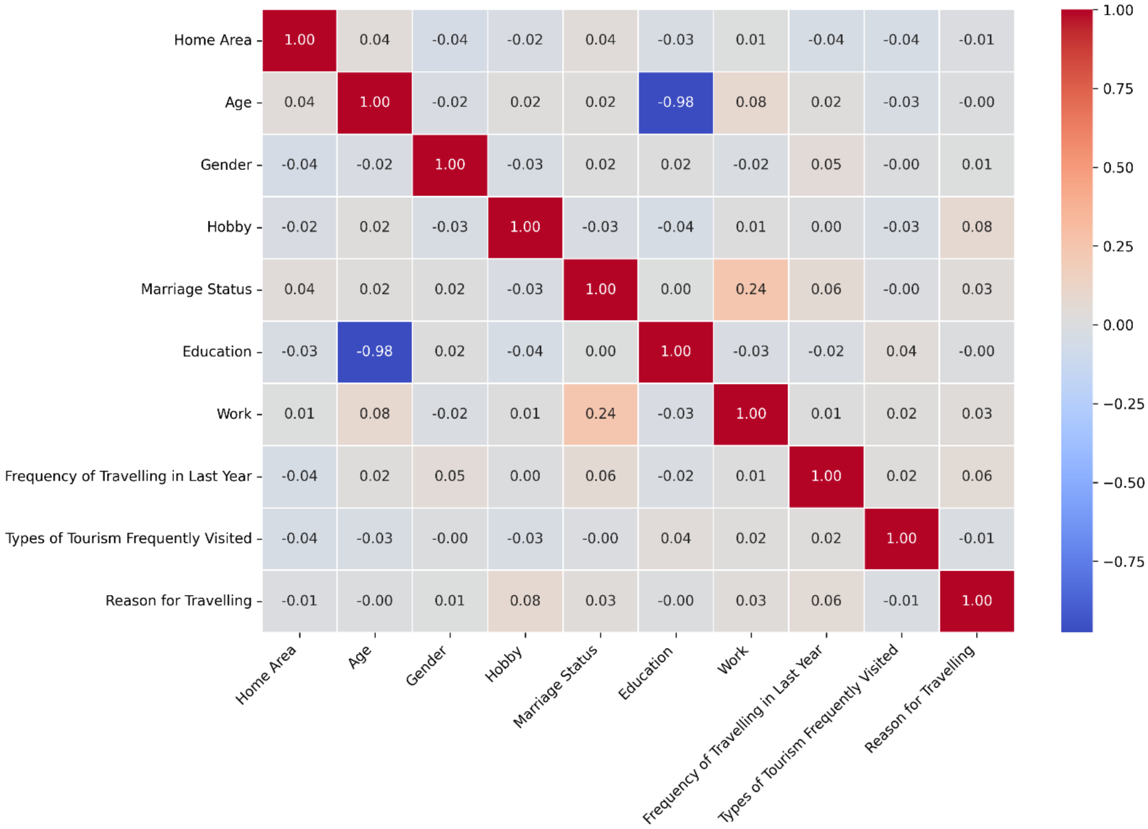

Figure. 3 Heatmap of demographic features

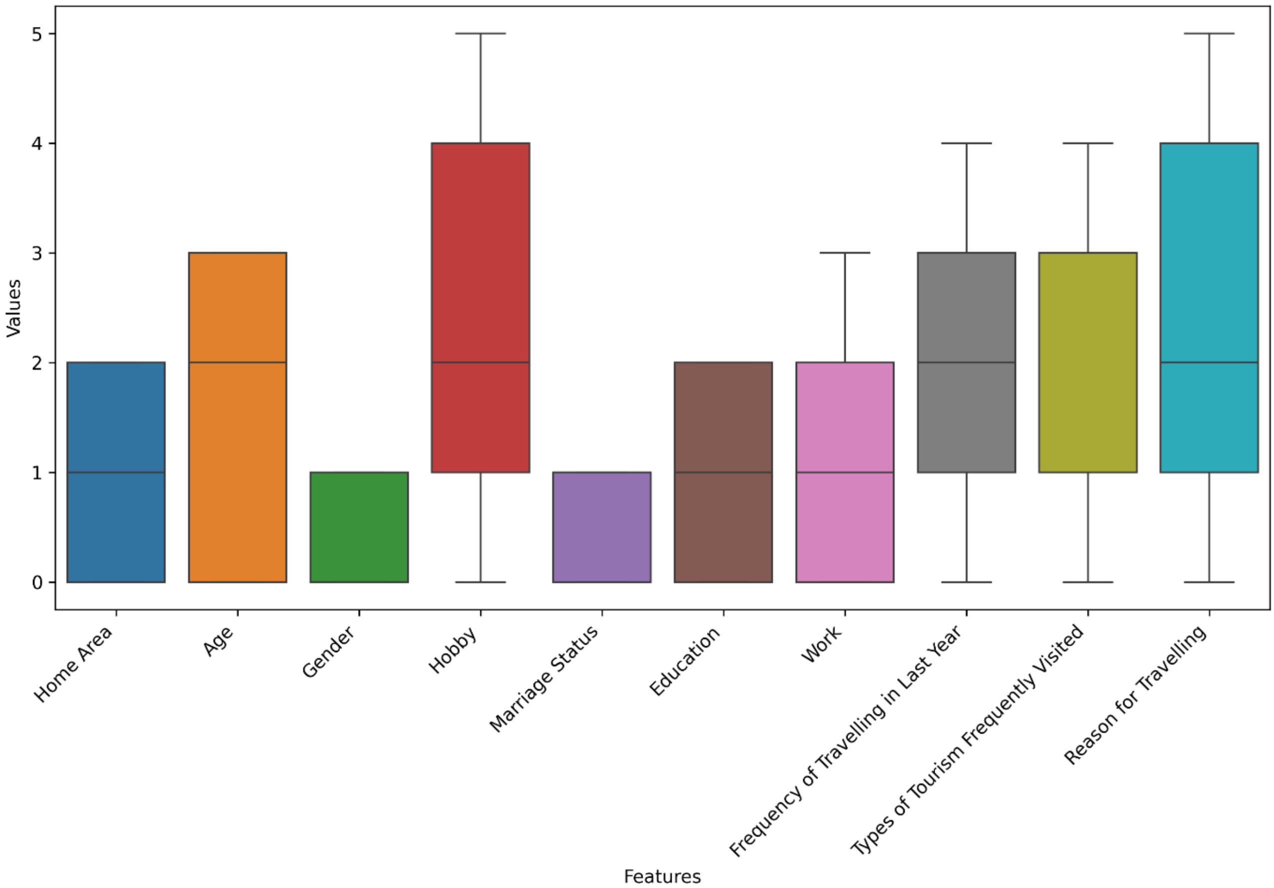

Figure. 4 Boxplot of demographic features

The relationship between demographic characteristics and destination choice was identified to improve the accuracy of recommendations. The system adjusts travel recommendations to user profiles more precisely. The results of the demographic feature analysis are shown in the heatmap diagram in Fig. 3 and the boxplot diagram in Fig. 4. This visualization helps the system in interpreting the pattern of relationships between variables. With this approach, the system can provide more relevant recommendations.

Fig. 3 shows the heatmap of correlation between demographic features in the research dataset. The system calculates the correlation coefficient to show the relationship between each feature pair. Correlation values ranged from -1 to 1, with red indicating a strong positive correlation and blue indicating a strong negative correlation. The age and education features had a high negative correlation (-0.98), which suggests that the older the age, the lower the education level in this dataset. In contrast, the marital and employment status features had a positive correlation (0.24), indicating that the employment factor could be related to the user's marital status. This heatmap helps the system in selecting the most relevant features for the recommendation model based on the relationships between variables.

Fig. 4 displays a feature boxplot in the dataset to analyze the distribution and variation of attribute values. The boxplot shows the minimum, first quartile, median, third quartile, and maximum values for each feature. The hobbies and travel reasons feature has a wider variety of values than other features, showing a wide range of preferences in the dataset. In contrast, gender features and marital status have a narrower distribution, which indicates a more limited number of categories. The age and travel frequency features show a more even distribution, with the median value being in the middle of the data range. The system uses these visualizations to understand data distribution patterns and identify possible outliers. With this information, the system can optimize data processing in the tourism recommendation model.

4.2 Model performance

The model performance evaluation subsection presents evaluation metrics that are used to measure the accuracy of the recommendation system. These analyses include accuracy, precision, recall, and F1-

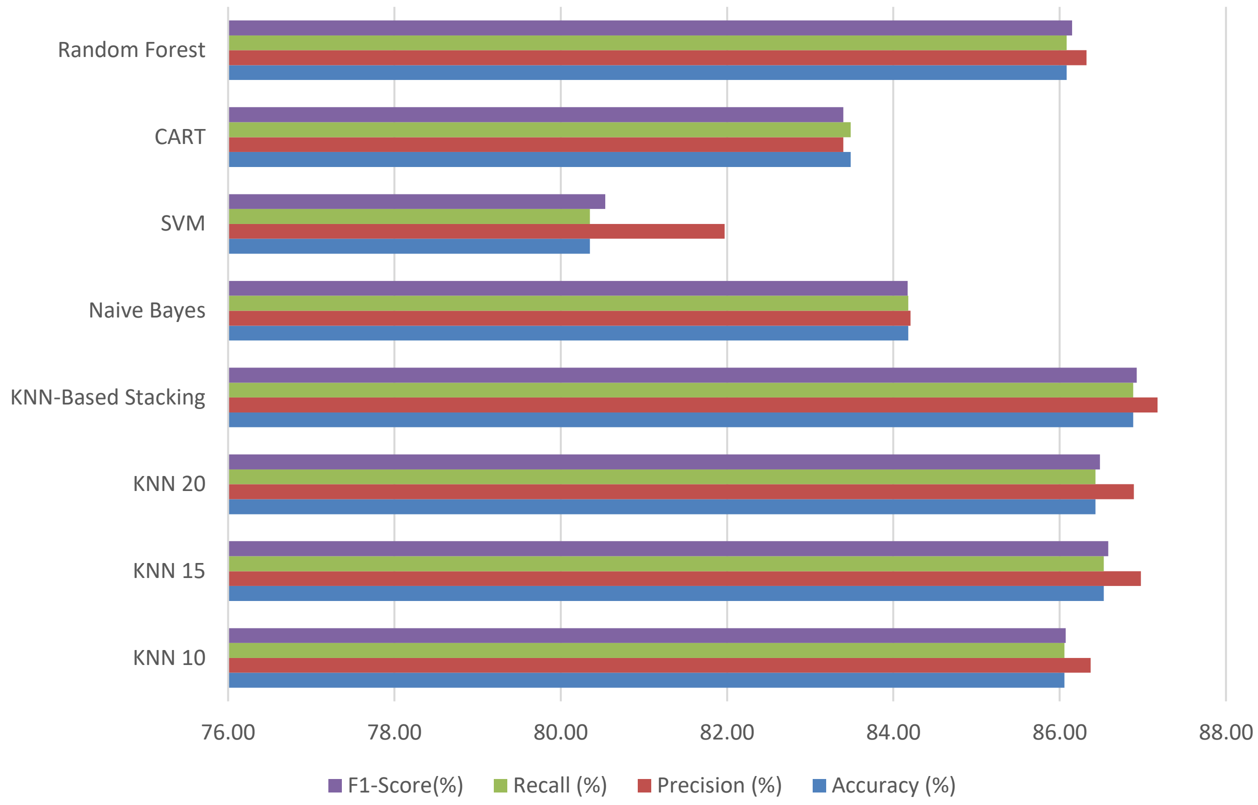

Figure. 5 Graph of test results

score, which compares the effectiveness of the KNN-Based Stacking model with other algorithms. The system tests the proposed model using an experimental dataset to ensure increased accuracy of tourism destination recommendations. The results of the evaluation show that this model has better performance than conventional methods. The graph in Fig. 5 shows a comparison of the evaluation results of the various models tested. This visualization helps the system in analyzing the advantages of the model based on the evaluation metrics used. We used these results to optimize the performance of the recommendations in this study.

Fig. 5 shows a comparison of the performance of machine learning models based on accuracy, precision, recall, and F1-score. The KNN-Based Stacking model shows the best performance with the highest score in all metrics compared to other models. KNN models with k variations (k=10, k=15, and k=20) have good performance, but are still below KNN-Based Stacking. The Random Forest and Naïve Bayes algorithms show competitive performance, albeit lower than KNN-Based Stacking-based models. CART and SVM models have lower accuracy, with less than optimal performance in other metrics. This graph helps the system in determining the best model based on the results of the performance evaluation. With this information, the system can optimize model selection to improve the accuracy of travel recommendations.

4.3 Comparison with several related research references

The position of this study on other related studies in the context of the tourism destination recommendation system is detailed in Table 3.

Table 3 details the position of this study in the tourism destination recommendation system by comparing the results with related studies. The KNN-Based Stacking model achieves an accuracy of 86.89%, precision of 87.18%, recall of 86.89%, and F1-score of 86.93%, which shows high performance in travel recommendations. The study by Arif et al. [10] used the MCRS, but only achieved an accuracy of 60%, lower than this model. Research by Fahrizal et al. [8] optimized the recommendation system with Neural Networks, but did not list accuracy as an evaluation metric. These results show that the KNN-Based Stacking model has an advantage in accuracy over other methods.

The study by Meng et al. [11] applied CNN-BiLSTM, which resulted in an accuracy of 85.10%, still below the proposed model.

Table 3. Comparison of this research with other tourism recommender systems

Study	Focus	Method	Evaluation Results			
			Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Arif et al. [10]	Halal tourism game recommendations	MCRS	0,60	0,67	0,64	0,65
Fahrizal et al. [8]	Tourism destination recommendations based on user data and destination characteristics.	Optimized with neural networks	-	0,62	0,97	0,76
Meng et al. [11]	Text Classification in Smart Tourism	CNN-BiLSTM	85,10	87,90	88,34	85,41
Ours	Tourism recommender system based on user demographic data	KNN-Based Stacking	86,89	87,18	86,89	86,93

This comparison proves that KNN-Based Stacking is superior in accuracy and other evaluation metrics. This advantage shows the effectiveness of the KNN-based ensemble approach in the tourism recommendation system. The results of this study contribute to the development of more accurate recommendation methods. These findings also open up opportunities for further exploration in a demographic data-based recommendation system.

5. Conclusions and future work

This study proposes KNN-Based Stacking as a new approach in the tourism destination recommendation system based on demographic data. This model integrates the variation of the number of neighbors in the KNN (k=10, k=15, and k=20) to improve the prediction accuracy. The evaluation results show that this model achieves an accuracy of 86.89%, precision of 87.18%, recall of 86.89%, and F1-score of 86.93%, higher than Random Forest, CART, SVM, and Naïve Bayes. Correlation analysis and data distribution confirm that demographic features play an important role in determining travelers' preferences. Compared to previous studies, this model shows superiority in the accuracy and effectiveness of recommendations.

Several developments can be made to improve the performance of the recommendation system. First, the system can be expanded by integrating data from social media or user reviews to improve the quality of predictions. Second, deep learning implementations, such as RNN (Recurrent Neural Networks) or Transformer-based models, can help address more complex patterns of traveler preferences. Third, the use of blockchain technology can create a more transparent and secure recommendation system. Finally, experimenting with hybrid recommendation methods that combine content-based filtering and collaborative filtering can improve recommendation personalization. With this development, the travel recommendation system can become more accurate, efficient, and responsive to user needs.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Author Contributions

Conceptualization, I. Marzuki, M. Hariadi; Methodology, I. Marzuki, Y.M. Arif, R.F. Rachmadi, M. Hariadi; Software Development, I. Marzuki, D. Hindarto, F.N. Fiqri; Validation, I. Marzuki, Y.M. Arif, R.F. Rachmadi, M. Hariadi; Formal Analysis, I. Marzuki, F.N. Fiqri, Nurhidayati, M. Hariadi;

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Acknowledgments

The author really appreciates the financial support from the Indonesian Education Scholarship (BPI), the Education Fund Management Institute (LPDP) and the Center for Higher Education Financing and Assessment (PPAPT) Ministry of Higher Education, Science, and Technology of Republic Indonesia. This funding plays a crucial role in facilitating research activities, obtaining critical resources, and ensuring the successful completion of these studies. The continued support from BPI, LPDP and PPAPT demonstrates their commitment to advancing research and encouraging academic excellence. The authors acknowledge their invaluable contribution, which significantly improves the quality and impact of this research.

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Received: January 6, 2025. Revised: March 5, 2025.

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