iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 Issue: V Month of publication: May 2025

DOI: https://doi.org/10.22214/ijraset.2025.70873

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue V May 2025- Available at www.ijraset.com

Smart City Exploration: A Reviews-Based Place Recommendation System

Ayush Meshram[1], Sushant Langhi[2], Kartik Kirve[3], Jatin Yadav[4], P.T.Kohok[5]
[1, 2, 3, 4]Student, [5]AssistantProfessor, Department of Computer Engineering, Pune Institute of Computer Technology, Pune, India

Abstract*: The expansion of cities has created a demand for advancedsystemsthatcanaidresidentsandtouristsinnavigating urban areas. This paper introduces a recommendation system that aims to improve the city exploration experience by utilizinga review-based approach. By analyzing user-generated reviews, sentiment analysis, and location/place data, the system suggests points of interest, enhancing decision-making for users [3] [4]. Thesystemusesmachinelearningmethods,suchascollaborative filteringandnaturallanguageprocessing,toanalyzeinformation. By considering both location-specific details and the sentiment conveyed in reviews, the approach guarantees that recommenda- tionsaresuitedtothespecificneedsandpreferencesoftheuser.

Index Terms: Recommendation System, Sentiment Analysis, Machine Learning, Collaborative Filtering, Natural Language Processing, Personalized Recommendations, User Reviews.

I. INTRODUCTION

A. Cities and Urbanization

Intheeraofdigitaltravelplanning,usersincreasingly rely on platforms like TripAdvisor, Google Maps, and Lonely Planettoexploreplacesandbuilditineraries.Whiletheseplat- formsoffergeneralsuggestionsandpopularlistsofattractions, they fall short in delivering truly personalized, context-aware recommendations. Our project addresses that gap by buildingasmartplacerecommendationsystemthatempowersusers to discover destinations tailored to their specific needs. Users can explore cities or regions based on their chosen place types (e.g., nature, historical, restaurants), apply a diverse set of 20–30 filters (such as wheelchair access, parking availability, restroom facilities, pet-friendliness), and select locations of interest. What sets this system apart is the integration of sentiment analysis on real user reviews, enabling the platform torankandrecommendlocationsnotjustbasedonpopularity, but on how positively people feel about them.

B. Impact of Recommendation Systems for City Exploration

Recommendation systems are widely implemented across various domains such as e-commerce, entertainment, and travel,helpingusersnavigatevastinformationlandscapeswith ease [1]. These systems can play a crucial role in simplifying decision-making by curating relevant points of interest based on individual needs. By analyzing user inputs, historical trends, and content such as reviews or ratings, these systems canenhanceusersatisfactionandengagement.Ourrecommen- dationsystemuses differentmethods,includingcollaborative filtering, content-based filtering, and hybrid approaches, to analyze data and offer personalized recommendations [5]. Usinguser-generatedcontent,suchasplacemetadata,reviews and ratings, our system can provide highly personalized and relevant recommendations [6].

As users share their opinions on the suggested places, a continuous feedback loop guarantees that the system becomes morepreciseandinsyncwiththeuser'spreferences,resulting in a more intuitive and enjoyable experience for city explo- ration. Despite the abundance of apps and services, finding yourwayaroundacitycanstillbeoverwhelming,particularly when taking into account the wide range of user preferences and the expansive nature of urban spaces. While traditional maps and static guides provide basic navigation, they fail to consider individual interests, making them less valuable for those seeking a personalized experience. For visitors, tailored suggestions can assist them in maximizing their limited timein the city, while for locals, the system can propose activities or services that improve their everyday life.

II. METHODOLOGY

The methodology follows a systematic approach to process and analyze raw data, detect fake reviews, and generate accu- rate recommendations. The entire workflow involves several stages, starting from data collection and cleaning to imple- mentation the final recommendation system.

A. Data Collection

The dataset used in this study was compiled through a combination of the Google Maps API and web scraping techniques, and was stored [14]. It includes key information suchasplacenames,businesscategories,userreviews,ratings, and other associated metadata.

Source:GoogleMaps(viaOutscraperAPI)

Collected Attributes:

- Basicdetails:name,type,subtypes,rating, user_ratings_total
- Locationinfo:borough,address,coordinates
- Reviews: reviews, review_score, review_link, review_time
- Metadata:Nestedfieldslikeabout(e.g.,parking, wheelchair access,toilet availability)

B. Data Cleaning and Filtering

1) *Initial Cleaning:*

- Dropped redundant columns (e.g., address, coords, description) that were either noisy or not useful for model training.
- Removed rows with missing or null values in essential fields such as reviews, subtypes, and rating.
- Convertedalltextdatatolowercasetoensureconsistency inprocessing.

ToolkitsUsed:pandas,numpy

2) *Filtering for Review-Rich Entries:*To ensure sentiment analysis was meaningful, we filtered out places with fewer than 100 reviews. This threshold was empirically chosen to maintain a balance between data quality and sample size.

- Rationale: A higher number of reviews increases confi- dence in aggregate sentiment polarity and user satisfaction.
- Impact: Reduced dataset size while improving the reliabil- ity of sentiment-based recommendations.

3) *Subtypes Text Preprocessing:*The subtypes col- umn(e.g.,"vegetarianrestaurant","historic site") was critical for understanding semantic content.

Steps:

- Tokenizedandlowercasedthetext.
- Removedpunctuationandnumericvalues.
- EliminatedstopwordsusingNLTK.
- *Optional:*Performedstemming/lemmatizationforim- proved vector representation (experimented with both).

Example:

- *Raw:* ["VegetarianRestaurant", "Family-Friendly Spot"]
- *Cleaned:* ["vegetarian","restaurant","family","friendly","spot"]

4) *Word Embedding Generation (Word2Vec):* Trained a Word2Vec model using the cleaned subtypes tokens to gen- erate 50-dimensional word vectors.

For each place, the average of its token embeddings was computed to obtain a single vector representation.

LibraryUsed:gensim.models.Word2Vec

ModelParameters:

Word2Vec(sentences=tokenized_data, vector_size=50, window=5, min_count=1, sg=1)

These embeddings served as numeric features for the Ran- dom Forest classifier.

C. Text Preprocessing and Word2Vec Embeddings

The textual data, primarily composed of user reviews, undergoesseveralpreprocessingstepstoprepareitformachine learningtasks.First,alltextisconvertedtolowercasetoensure uniformity, and non-alphabetic characters such as punctuation marks and numbers are removed. Tokenization is then ap- plied, breaking each review into individual words. Common stopwords (e.g., ”and”, ”the”, ”is”) are eliminated as they do not provide meaningful insights for semantic understanding. Followingthis,stemmingorlemmatizationmaybeemployed to reduce words to their base forms, enhancing consistency across the corpus. Once the text is cleaned, the Word2Vec modelistrainedonthepreprocesseddata.Word2Vecgenerates dense vector embeddings for each word by analyzing its surrounding context within reviews [16]. This approach cap- turesthesemanticrelationshipsbetweenwordsandtransforms unstructured textual data into a meaningful numerical format, enabling effective input for subsequent stages such as place type classification and sentiment analysis.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue V May 2025- Available at www.ijraset.com

D. Category Classification Model

1) *Label Encoding of Place Types:* Mapped string-based type labels (e.g., "restaurant", "attraction") to nu- meric values using LabelEncoder. This transformed the output variable into a format suitable for machine learning algorithms.
2) *ModelTrainingusingRandomForest:*

- Splitdataintotrainingandtestsetsusingan80:20ratio.
- TrainedaRandomForestClassifierusingWord2Vec vectors as input features.
- ClassifierUsed:sklearn.ensemble.RandomForestClassifier
- KeyHyperparameters:

n_estimators=100,max_depth=None,random_state=42

3) *Evaluation of Classifier:*Measured accuracy, precision, and recall on the test dataset. Sample test predictions were manually inspected to validate semantic consistency.

Expected Accuracy:80–90% (varies by place diversity and embedding quality)

E. Fake Review Removal and Sentiment Analysis

1) *Fake and Redundant Review Detection:*Applied heuris- tic rules to clean the review dataset:

- Heuristic1:ExcessiveSentiment—Reviewscontaining overly positive language and repetitive keywords (e.g., "best", "awesome") were flagged as possibly inau- thentic.
- Heuristic2:Duplication—Reviewswithidenticaltitles and content were considered redundant and removed.
- Heuristic 3: Outliers — Reviews with unusually short (<5words)orexcessivelylong(>300words)textwere flagged as unnatural.

LibrariesUsed:TextBlob,re,andnltk

2) *Sentiment Polarity Scoring:* Used TextBlob, alexicon-basedsentimentanalyzer,tocalculatepolarityforeach review [3].

PolarityRange:[−1,1] —Negative(below0),Neutral(0),
Positive(above0)
Eachreviewwaslabeledas:

- positiveifpolarity>0.1
- negativeifpolarity<-0.1
- neutralotherwise

Thisgeneratedanewfieldsentiment_score,which was later used to rank places based on user perception.

F. Feature Extraction from Nested JSON(about)

1) *FlatteningandParsingJSONFields:*Theabout field(e.g.,*{*’wheelchair_accessible’:True, ’parking’:False*}*) was parsed using json.loads. Individual boolean columns were created for each key, such as:

- has_parking
- has_toilets
- wheelchair_accessible

2) *HandlingMissingValues:*AnymissingorNoneentries in the aboutfield were set to False, interpreting the absence of information as unavailability of that feature.

Purpose:Enabledbooleanfilteringforpersonalizedrecom- mendations (e.g., show only places with wheelchair access).

G. System Design

The final recommendation system is deployed as a Flask- based web application. User authentication features, including Google OAuth, are integrated to allow secure access to the system. The recommendation system leverages the processed data to suggest relevant places to users based on their prefer- ences. The application also integrates Leaflet.js for interactive map visualization, allowing users to view recommendationson a map and filter them according to different criteria.

III. IMPLEMENTATION

A. Data Collection

Objective: Collectdatafromvarioussourcestobuilda comprehensive dataset for analysis.

TechnologiesUsed:
- Python:Forscriptinganddatamanipulation.
- Pandas:Fordatahandlingandanalysis.
- ExcelFiles:Astheprimarydatasource.

Process: Data is collected from multiple Excel files: outscraper_first.xlsx, data_pos.xlsx, and data_neg.xlsx. The dataset includes information about places, reviews, and additional metadata for analysis.

B. Data Preprocessing

Objective:Cleanandpreprocessthedatasettomakeit suitable for analysis and modeling.
TechnologiesUsed:
- Pandas:Fordatamanipulationandcleaning.
- NumPy:Fornumericaloperations.

Process:
- LoadData:LoadthedatasetfromExcelfiles.
- CheckforNullValues:Identifyandhandlecolumns with null values.
- Remove Unnecessary Columns: Drop columns that are not relevant for the analysis.
- FilterRows:Removerowswithnullvaluesincritical columns.
- SaveCleanedData: Save the cleaned dataset to a new Excel file (data500.xlsx).

C. SentimentAnalysis

Objective: Perform sentiment analysis on reviews to clas- sify them as positive, negative, or neutral.
TechnologiesUsed:
- TextBlob:Forsentimentanalysis.
- Pandas:Fordatamanipulation.

Process:
- LoadData:Loadthedatasetcontainingreviews.
- Sentiment Analysis: Use TextBlobto calculate the sentiment score of each review [4].
- Classify Reviews: Classify reviews based on their senti- ment score.
- SaveProcessedData:Savetheprocesseddatasetwithsentimentscorestonew Excelfiles (pos_processed_reviews.xlsx, neg_processed_reviews.xlsx).

D. Fake Review Detection

Objective: Detect and remove fake reviews based on vari- ous indicators.
TechnologiesUsed:
- Pandas:Fordatamanipulation.
- TextBlob:Forsentimentanalysis.

Process:
- LoadData:Loadtheprocessedreviewdatasets.
- Detect Fake Reviews: Detect reviews with excessive sentiment,duplicatereviews,andreviewswithsuspicious lengths.
- CombineIndicators:Combineallfakereviewindicators to flag fake reviews.
- Remove Fake Reviews: Remove flagged fake reviews from the dataset.
- SaveCleanedData:Savethecleaned datasetwithoutfakereviewstonewExcel files (cleaned_pos_reviews.xlsx, cleaned_neg_reviews.xlsx).

E. Data Expansion and Transformation

Objective: Expand and transform JSON data into a tabular format.
TechnologiesUsed:
- Pandas:Fordatamanipulation.

- JSON:ForhandlingJSONdata.

Process:
- LoadData: Load thedataset containing JSON data(e.g.,aboutcolumn).
- ExpandJSONData:ConverttheJSONdataintoa dictionary and flatten it.
- Merge withPlace ID: Merge theexpanded data with theplace_idcolumn.
- SaveTransformedData:Savethetransformeddatato a new Excel file (about_expanded.xlsx).

F. Data Storage
Objective:Insertthecleanedandtransformeddataintoa MySQL database.
TechnologiesUsed:
- MySQL:Fordatabasestorage.
- Python(mysql-connector):Fordatabaseconnectivity.
- Pandas:Fordatamanipulation.

Process:
- ConnecttoMySQL:EstablishaconnectiontotheMySQL database.
- CreateTable:Createatabledynamicallybasedonthe DataFrame structure.
- Insert Data: Insert the DataFrame data into the MySQL table, ensuring proper handling of NaN values.

G. Recommendation Engine
Objective:Developarecommendationsystemtosuggest places based on user preferences.
TechnologiesUsed:
- Python:Forscriptinganddatamanipulation.
- Pandas:Fordatahandling.
- Scikit-Learn:Formachinelearningalgorithms.
- Gensim(Word2Vec):Fortextvectorization.

Process:
- TextPreprocessing:Converttextdataintonumerical vectors using Word2Vec [16] [17].
- TrainClassifier:TrainaRandomForestclassifieronthe training data [?].
- EvaluateModel:Evaluatethemodel'saccuracyonthe test data.
- RecommendationLogic: Use the trained model to rec- ommend places based on user preferences and filters.

H. Web Application
Objective: Develop a Flask web application for user inter- action and recommendations.
TechnologiesUsed:
- Flask:Forwebapplicationdevelopment.
- HTML/CSS/JavaScript:Forfrontenddevelopment.
- Bootstrap:Forresponsivedesign.
- Leaflet:Formapvisualization.
- GoogleOAuth:Foruserauthentication.

Process:
- Initialize Flask App: Set up the Flask application and define routes.
- User Authentication: Implement signup, sign-in, and Google OAuth functionalities.
- Recommendation System: Integrate the recommenda- tion engine to suggest places based on user preferences [2].
- Map Integration: Integrate Leaflet.js for map visualiza- tion of recommended places.
- Frontend Development:UseBootstrapforthefrontend, implementJavaScriptfordynamicinteractionsandAJAX requests.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue V May 2025- Available at www.ijraset.com

IV. RESULTS AND DISCUSSION

A. Data Collection and Preprocessing

1) Accuracy:

- Data Sources: The system collects data from reliable sources such as the Google Places API and pre-collected Excel files, ensuring that the dataset is comprehensive and up-to-date.
- Data Cleaning: Preprocessing steps, including handling null values, removing unnecessary columns, and filtering rows, ensure that the dataset is clean and relevant for analysis.
- SentimentAnalysis:UsingTextBlobforsentimentanal- ysis allows for accurate classification of reviews as posi- tive,negative,orneutral,whichiscrucialforunderstand- ing user preferences and feedback.
- FakeReviewDetection:Detectingandremovingfakere- viewsbasedonvariousindicatorsensuresthatthedataset remains reliable and free from biased or manipulateddata.

2) Effectiveness:

- ComprehensiveData:Thecombinationofdatafromthe GooglePlacesAPIandpre-collectedExcelfilesprovides a rich dataset for analysis.
- CleanData:Thepreprocessingstepsensurethatthedata is clean, which in turn improves the accuracy of the recommendation engine.
- Sentiment Analysis: Accurate sentiment analysis helps inunderstandinguserpreferencesandfeedback,ensuring relevant recommendations.
- FakeReviewDetection:Removingfakereviewsensures that the recommendations are based on genuine and reliable data.

B. Recommendation Engine

1) Accuracy:

- Text Vectorization:UsingWord2Vecfortextvectoriza- tion ensures that text data is accurately converted into numericalvectors,whichisessentialformachinelearning algorithms.
- MachineLearningModel:TheRandomForestclassifier is trained on the preprocessed data to classify places by type,withevaluationmetricssuchasaccuracyscoreused to assess its performance.
- Collaborative Filtering: Collaborative filtering tech- niques ensure personalized recommendations based on user preferences and past interactions.

2) Effectiveness:

- Personalized Recommendations: The recommendation engine generates personalized suggestions based on user preferences and interactions.
- Accurate Classification: The Random Forest classifier accuratelyclassifiesplacesbasedontheirtype,improving the relevance of the recommendations.
- Collaborative Filtering: The use of collaborative filter- ing enhances the recommendations by considering the preferences of similar users [13].

C. User Feedback Analysis

1) Accuracy:

- Sentiment Analysis: TextBlob is used to classify user feedback as positive, negative, or neutral, ensuring that feedback is accurately analyzed.
- FeedbackIntegration:Integratinguserfeedbackintothe recommendationenginehelpsimprovefuturerecommen- dations.

2) Effectiveness:

- Continuous Improvement: The system continuously refines its recommendations based on user feedback, ensuring that suggestions remain relevant and accurate over time.
- User Satisfaction: Accurate sentiment analysis of user feedbackaidsinunderstandingusersatisfactionandareas for improvement, enhancing the system’s overall effec- tiveness.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue V May 2025- Available at www.ijraset.com

D. Web Application

1) Accuracy:

- UserAuthentication:Theimplementationofsecureuser signup, sign-in, and Google OAuth ensures safe data storage and access.
- Map Integration: Integrating Leaflet for map visualiza- tion ensures accurate display of recommended places on the map.

2) Effectiveness:

- User-Friendly Interface: The Flask web application provides a simple and intuitive interface for interaction, improving the user experience.
- Dynamic Interactions: JavaScript and AJAX enable dynamicinteractions,makingthewebapplicationrespon- sive and efficient.
- Map Visualization: Leaflet provides interactive map vi- sualizations that help users explore recommended places effectively.

E. Comparison with Existing Systems

1) ExistingSystems:

- Popular recommendation systems such as Google Maps, Yelp,andTripAdvisoruseadvancedalgorithmsandlarge datasets to provide recommendations.
- Many systems rely on collaborative filtering and senti- ment analysis to improve recommendation accuracy [7] [9].

2) ImplementedSystem:

- Comprehensive Data Collection: Data from the Google Places API and Excel files ensures the dataset is compre- hensive and up-to-date.
- Accurate Data Preprocessing: The preprocessing steps, including sentiment analysis and fake review detection, ensure the data is reliable.
- Effective Recommendation Engine: Machine learning and collaborative filtering ensure personalized and rele- vant recommendations.
- UserFeedbackAnalysis:Continuousintegrationofuser feedback enhances the system’s effectiveness.
- User-Friendly Web Application: The Flask web ap- plication enhances user experience through an intuitive interface and dynamic interactions.

F. ScreenShots

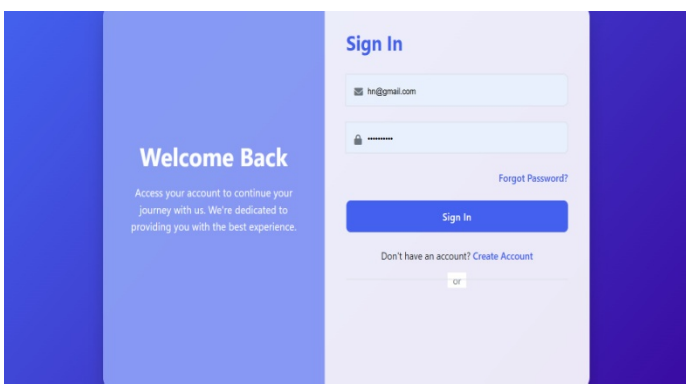


Figure1:Loginwebpage

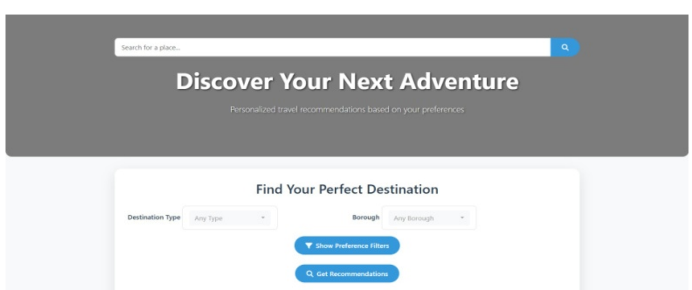


Figure2:Dashboardview

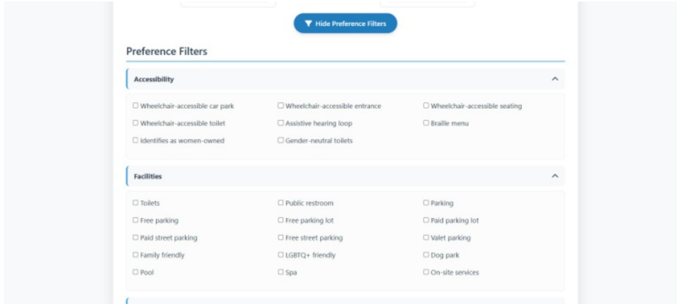


Figure3:Filterssection

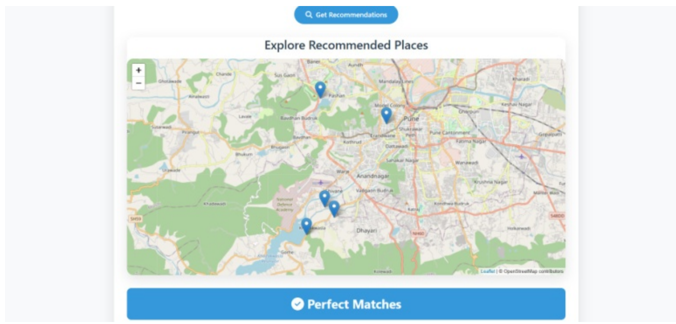


Figure4**:**LocationDisplayonmap

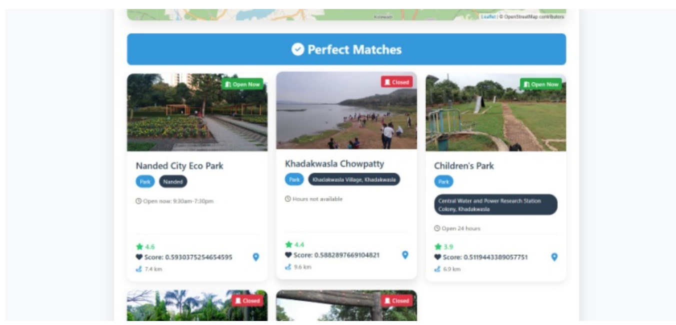


Figure5:ActualRecommendation

V. CONCLUSION

In this implementation, we developed a comprehensive travel recommendation system that leverages advanced data preprocessing,machinelearningalgorithms,anduserfeedback analysis to provide personalized and relevant recommenda- tions. The system architecture includes data collection from reliable sources, accurate data preprocessing, an effective recommendationengine,andauser-friendlywebapplication.

A. Summary of Implementation

1) DataCollectionandPreprocessing::

- Data Sources: Data was collected from the Google Places API and pre-collected Excel files, ensuring a comprehensive and up-to-date dataset.
- Preprocessing Steps: The dataset underwent rigorous preprocessing, including handling null values, removing unnecessarycolumns,sentimentanalysisusingTextBlob, and fake review detection.
- Text Vectorization: Text data was converted into nu- merical vectors using Word2Vec, making it suitable for machine learning algorithms.

2) RecommendationEngine::

- Machine Learning Model: A Random Forest classifier was trained to classify places based on their type, ensur- ing accurate classification.
- Collaborative Filtering: Collaborative filtering tech- niques were employed to provide personalized recom- mendations based on user preferences and past interac- tions.
- User Feedback Analysis: User feedback was contin- uouslyintegratedintotherecommendationengineto improve the accuracy and relevance of future recommen- dations.

3) WebApplication::

- User Authentication: User signup, sign-in, and Google OAuthfunctionalitieswereimplementedtoensuresecure user data storage and access.
- Map Integration: Leaflet was integrated for interactive map visualization of recommended places.
- User-Friendly Interface: The Flask web application provided a responsive and user-friendly interface for interaction and visualization, enhancing the overall user experience.

B. Improvements Over Existing Systems

1) *Comprehensive Data Collection::* The system collects data from multiple reliable sources, ensuring a rich and up-to-date dataset. Existing systems often rely on a single data source,whichmaylimitthecomprehensivenessofthedataset.
2) *AccurateDataPreprocessing::*Thepreprocessingsteps, includingsentimentanalysisandfakereviewdetection,ensure thatthedatasetiscleanandreliable.Existingsystemsmaynot employsuchrigorouspreprocessingsteps,leadingtopotential biases or inaccuracies in the dataset.
3) *Effective Recommendation Engine::* The recommenda- tionengineusesacombinationofmachinelearningalgorithms and collaborative filtering techniques to provide personalized and relevant recommendations. Existing systems may rely solely on collaborative filtering, which may not capture the nuances of user preferences as effectively [7].
4) *Continuous User Feedback Analysis::*The system con- tinuously improves its recommendations based on user feed- back, ensuring that the recommendations remain relevant and accurate over time. Existing systems may not integrate user feedback as effectively, leading to potential stagnation in recommendation quality.

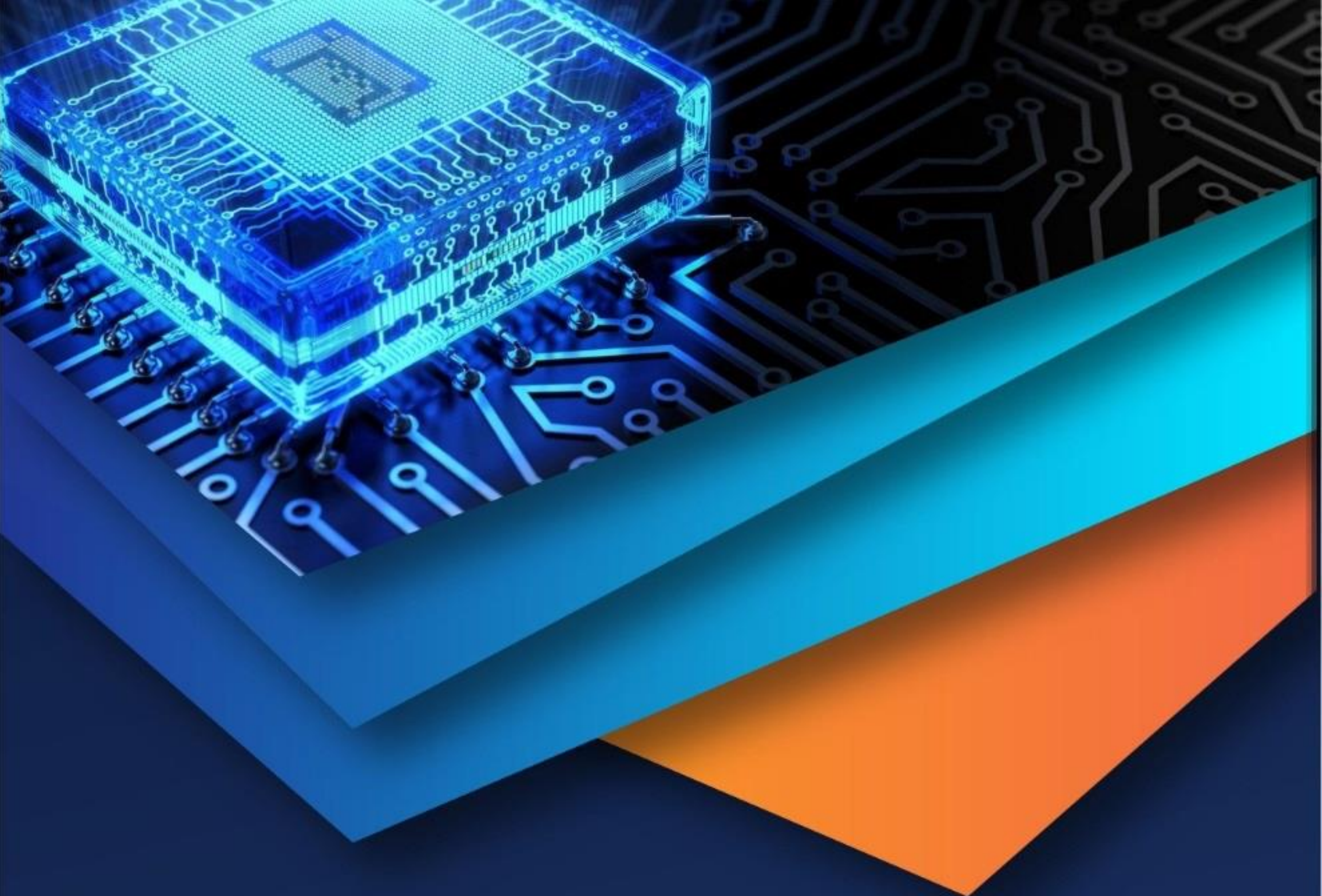
C. Future Work and Enhancements

1) AdvancedMachineLearningTechniques:Futurework couldexploreadvancedmachinelearningtechniquessuch as deep learning and reinforcement learning to enhance the accuracy and relevance of recommendations [10].
2) Real-Time Data Updates: Integrating real-time data updates from the Google Places API to ensure that the recommendationsarealwaysup-to-date.Dynamicdataset and recommendation updates could be implemented.
3) Enhanced User Feedback Analysis: Implement more advanced techniques for user feedback analysis, such as NLP,tobetterunderstanduserpreferencesandfeedback[11][12]
4) Scalability and Performance: Optimize the system for scalability and performance to handle a large number of users and recommendations efficiently. Implement load balancing and caching mechanisms to improve respon- siveness and efficiency.
5) User Interface Enhancements: Enhance the user in- terfacetoprovideamoreintuitiveandengaginguser experience. Implement additional visualization tools and interactive features to help users explore recommenda- tions more effectively.

REFERENCES

[1] Pu,Zihao&Du,Hongyu&Yu,Sizhe&Feng,Duanyu.(2020). Improved Tourism Recommendation System. 121-126.10.1145/3383972.3384074.
[2] Kawai, Yukiko & Zhang, Jianwei & Kawasaki, Hiroshi. (2009). Tourrecommendation system based on web information and GIS. 990 - 993.10.1109/ICME.2009.5202663.
[3] Osman, Nurul. (2020). Contextual Sentiment Based RecommenderSystem to Provide Recommendation in the Electronic Products Do-main. International Journal of Machine Learning and Computing. 9.10.18178/ijmlc.2019.9.4.821.
[4] Gong, Y. (2024). Research on recommendation algorithm based on usersentiment analysis. Proceedings of the 4th International Conference onSignal Processing and Machine Learning, 84-91.
[5] Zhang, H.-R., Min, F., He, X., & Xu, Y.-Y. (2015). A hybrid recom-mender system based on user-recommender interaction. MathematicalProblems in Engineering, 2015, Article ID 145636, 11 pages.

[6] Phan,Lan&Huynh,Hung&Huynh,Hiep.(2018).ImplicativeRating-BasedHybridRecommendationSystems.InternationalJour-nal of Machine Learning and Computing. 8. 223-228. 10.18178/i-jmlc.2018.8.3.691.
[7] S. M. Al-Ghuribi and S. A. Mohd Noah, ”Multi-Criteria Review-BasedRecommenderSystem–TheStateoftheArt,”inIEEEAccess,vol.7,pp.169446-169468,2019,doi:10.1109/ACCESS.2019.2954861.
[8] Ko,Hyeyoung&Lee,Suyeon&Park,Yoonseo&Choi,Anna.(2022).ASurvey of Recommendation Systems: Recommendation Models, Tech-niques, and Application Fields. Electronics. 11. 141. 10.3390/electron-ics11010141.
[9] Burke, Robin. (2002). Hybrid Recommender Systems: Survey andExperiments. User Modeling and User-Adapted Interaction. 12.10.1023/A:1021240730564.
[10] F.S¸eker,“EvolutionofMachineLearninginTourism:AComprehensiveReviewofSeminalResearch”,JournalofArtificialIntelligenceandDataScience, vol. 3, no. 2, pp. 54–79, 2023.
[11] Ma, S. (2024). Enhancing Tourists’ Satisfaction: Leveraging ArtificialIntelligence in the Tourism Sector. Pacific International Journal, 7(3),89–98.
[12] G.Linden,B.SmithandJ.York,”Amazon.comrecommendations:item-to-item collaborative filtering,” in IEEE Internet Computing, vol. 7, no.1, pp. 76-80, Jan.-Feb. 2003.
[13] Zheng, Yu & Xie, Xing & Ma, Wei-Ying. (2010). GeoLife: A Collabo-rative Social Networking Service among User, Location and Trajectory.IEEE Data Eng. Bull.. 33. 32-39.
[14] Onwuegbuzie, Anthony J., Nancy L. Leech, and Kathleen MT Collins.”Qualitative analysis techniques for the review of the literature.” Qual-itative Report 17 (2012): 56.
[15] Church,KennethWard.”Word2Vec.”NaturalLanguageEngineer-ing 23.1 (2017): 155-162.
[16] Ma, Long, and Yanqing Zhang. ”Using Word2Vec to process big textdata.” 2015 IEEE International Conference on Big Data (Big Data).IEEE, 2015.
[17] Tan, Kian Long, et al. ”RoBERTa-LSTM: a hybrid model for sentimentanalysiswithtransformerandrecurrentneuralnetwork.”IEEEAccess10(2022): 21517-21525.



10.22214/IJRASET

INDEX COPERNICUS
45.98

IMPACT FACTOR:
7.129

TOGETHER WE REACH THE GOAL

IMPACT FACTOR:
7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY