BeachRecs: A Coastal Tourism Navigation System with Integrated Safety Alerts

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Abstract: BeachRecs-India presents a novel AI- and ML-driven platform designed to enhance coastal tourism safety in India by providing actionable beach safety insights through a Smart Mobile and Web Application. Unlike real-time monitoring systems, BeachRecs relies on pre-processed tidal and weather data to generate a predictive Beach Safety Index, helping tourists make informed decisions. The system also integrates a user-friendly interface and a chatbot for tourism assistance, delivering a holistic solution for beachgoers. Future enhancements include global deployment, advanced Natural Language Processing for improved user interaction, and optional integration with Wearable Devices for non-continuous health and safety notifications. The developed platform demonstrates robust performance with an overall accuracy of 94.53%, validating its effectiveness in delivering reliable, data-driven beach safety guidance.

Keywords: *Coastal Tourism, Beach Safety, Artificial Intelligence, Machine Learning, Predictive Analytics, Smart Tourism, Chatbot, Non-Real-Time Data.*

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I. INTRODUCTION

The global tourism sector is a major contributor to economic development, accounting for significant employment generation and GDP growth worldwide. In recent years, the concept of Smart Tourism (ST) has emerged, integrating advanced technologies such as the Internet of Things (IoT), Big Data Analytics, Artificial Intelligence (AI), and real-time data processing to enhance tourism services and management [1]. Smart tourism systems aim to improve operational efficiency, enhance visitor experience, and promote sustainability through data-driven decision-making frameworks [2]. Among various tourism domains, coastal tourism represents a high-impact segment due to its substantial economic value and large influx of visitors. Coastal destinations attract millions of domestic and international tourists annually, significantly contributing to local economies [3].

However, coastal environments are inherently dynamic and prone to environmental uncertainties such as rip currents, tidal variations, storm surges, high wave activity, and sudden meteorological changes. These hazards pose serious safety risks, particularly in developing regions where real-time monitoring infrastructure and digital safety communication mechanisms are limited. India, with a coastline extending over 7,500 km across nine coastal states and four Union Territories, holds immense potential for coastal tourism. Despite this advantage, the absence of a unified and real-time digital framework for beach safety management remains a critical challenge. Existing platforms, including weather applications and navigation systems, primarily provide static or generalized information such as location details, user reviews, and basic weather forecasts. They lack location-specific hazard intelligence, predictive safety alerts, and integrated coastal risk analytics, which are essential for ensuring tourist safety.

The lack of real-time safety communication has contributed to a significant number of beach-related accidents and drowning incidents, often caused by delayed awareness and in-sufficient risk dissemination. Additionally, tourists face challenges in accessing reliable information regarding beach conditions, available amenities, and safety infrastructure. Current applications also fail to establish effective integration with local authorities and disaster management systems, resulting in delayed or inefficient communication of critical alerts. These limitations highlight the need for a comprehensive, intelligent, and user-centric solution that can bridge the gap between environmental risk data and public accessibility.

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To address these challenges, this paper proposes BeachRecs-India, a smart mobile and web-based application designed to provide AI-driven, real-time coastal safety recommendations. The proposed system integrates heterogeneous data sources, including live meteorological data, tidal information, environmental sensors, and disaster alerts. By leveraging AI-based risk assessment models and geospatial analytics, the platform generates location-aware safety advisories and personalized recommendations for beachgoers. The system aims to enhance situational awareness, improve safety outcomes, and support informed decision-making for tourists, thereby contributing to safer and more efficient coastal tourism management.

II. LITERATURE REVIEW

Smart tourism has emerged as a dynamic and rapidly evolving research domain that integrates digital technologies, artificial intelligence (AI), and the Internet of Things (IoT) to enhance visitor experiences, improve operational efficiency, and facilitate sustainable management in tourism destinations. Gretzel et al. [4] laid the foundational understanding of smart tourism, highlighting its evolution, core components, and the critical role of digital platforms in enabling personalized, seamless, and context-aware travel experiences. The study emphasized how data-driven insights and intelligent systems can transform traditional tourism into a highly interactive and responsive environment. Building upon this, Koo et al. [5] provided a comprehensive 10-year retrospective on AI-powered smart tourism, presenting an updated model that emphasizes predictive analytics, intelligent recommendation systems, and the integration of data-driven decision-making processes for modern tourism management. This work underlines the importance of leveraging historical and behavioural data to anticipate tourist needs and enhance service delivery across diverse destinations. The aspect of visitor safety, particularly in coastal and beach areas, has been a significant concern in tourism research. Castelle [6] examined rip current hazards and coastal safety measures, emphasizing the critical need for accurate risk assessment, hazard mapping, and preventive strategies to reduce accidents in beach environments. Similarly, Kontogianni and Alepis [7] reviewed recent advances in smart tourism over the last six years, analyzing technological trends, safety applications, and the implementation of IoT-driven monitoring systems for real-time and predictive hazard management. Their work highlights the growing adoption of sensor networks, automated alerts, and mobile platforms to ensure safer travel experiences, especially in high-risk areas. Practical applications of smart tourism technologies in enhancing beach safety have been demonstrated through mobile and IoT-based platforms. Peña-Abreu and Terroso-Saenz [8] introduced “Beach and Weather,” a mobile crowdsensing system that allows tourists to report and access local beach conditions, providing timely and actionable safety information. Complementing this, Pelegrí-Sebastiá et al. [9] developed a robust IoT system for smart beach applications, validating its effectiveness through a detailed case study in the Valencian Region, Spain. Islam et al. [10] further contributed by proposing an IoT-enabled water quality monitoring system that leverages machine learning algorithms to predict and manage risks, supporting tourist safety and health management. Collectively, these studies demonstrate that the combination of IoT, mobile platforms, and predictive analytics can provide both preventive and informative safety measures for beachgoers. Beyond technology-driven safety solutions, operational efficiency and human resource management remain critical components of effective tourism management. Sánchez-Sánchez et al. [11] applied a Data Envelopment Analysis (DEA)-based approach to evaluate labour efficiency in rural hotels, offering valuable insights into optimizing workforce performance and resource allocation. Chandra et al. [12] explored the challenges in online hospitality and tourism education, identifying gaps in curriculum design, digital learning adoption, and technological preparedness among students and institutions. Bashir et al. [13] conducted a bibliometric analysis to map the foundations and trends in tourism research, revealing evolving priorities such as sustainability, digital transformation, smart tourism infrastructure, and the increasing relevance of AI and IoT in operational and experiential contexts.

Overall, these studies collectively demonstrate that the integration of AI, IoT, and data-driven analytics is transforming tourism experiences, improving visitor safety, operational efficiency, and educational frameworks. However, there remains significant scope for combining predictive analytics, smart beach safety systems, and intelligent educational platforms into holistic solutions that simultaneously address tourist satisfaction, safety, and operational management. Such integrative approaches can foster smarter, safer, and more sustainable tourism ecosystems in both coastal and inland destinations.

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III. PROPOSED SYSTEM ARCHITECTURE

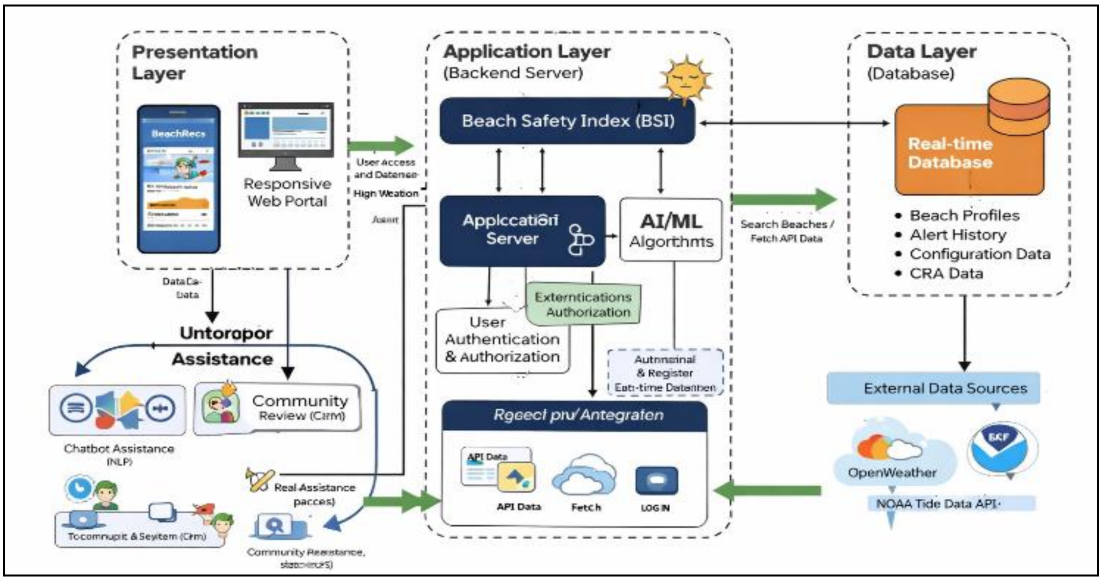

Fig 1 BeachRecs: System Architecture

The proposed BeachRecs system is designed using a scalable and modular architecture to efficiently support real-time coastal safety monitoring and recommendation services. The architecture follows a microservices-oriented approach, enabling independent development, deployment, and scalability of system components. This design ensures high availability, fault tolerance, and efficient handling of dynamic data streams originating from multiple heterogeneous sources.

The architecture is logically divided into three primary layers: the presentation layer, the application layer, and the data layer. The presentation layer serves as the user interaction interface and is implemented through both mobile and web-based platforms. It is designed to provide a responsive and intuitive user experience, ensuring quick access to critical information such as safety alerts, beach conditions, and the computed Beach Safety Index (BSI). The interface emphasizes simplicity and clarity, allowing users to easily navigate through features such as beach search, real-time alerts, chatbot assistance, and community reviews.

The application layer acts as the core processing unit of the system and is responsible for executing business logic, handling user authentication, and managing communication between frontend interfaces and backend services. This layer integrates multiple modules, including API management, data processing, and AI-driven analytics. The backend continuously collects real-time data from external sources such as meteorological services, tidal information systems, and environmental monitoring platforms. These inputs are processed using machine learning models and rule-based algorithms to compute the Beach Safety Index, which represents the overall safety condition of a particular coastal location. The application layer also generates real-time alerts and emergency notifications based on predefined thresholds and predictive analytics, ensuring timely dissemination of critical information to users.

The data layer is responsible for persistent storage and efficient retrieval of system data. A real-time database system is utilized to support low-latency access and continuous updates. This layer maintains structured datasets, including beach profiles, historical environmental data, user information, alert logs, and configuration parameters for risk assessment models. The integration of both static and dynamic datasets enables accurate analysis and supports long-term trend evaluation for improved decision-making. Additionally, the system incorporates secure authentication mechanisms to ensure data integrity and controlled access to sensitive information.

A key aspect of the proposed architecture is the integration of external data sources through secure APIs. These sources include weather forecasting services, tidal data providers, and disaster alert systems, which continuously feed real-time information into the system. The integration layer ensures seamless communication and synchronization between external services and internal modules, thereby maintaining the accuracy and reliability of safety predictions. Furthermore, the system includes an intelligent chatbot module based on natural language processing, which provides interactive assistance to users by answering queries related to beach conditions, safety measures, and nearby facilities.

Overall, the proposed architecture provides a unified framework that combines real-time data acquisition, intelligent risk assessment, and user-centric service delivery. By leveraging scalable microservices, AI-driven analytics, and seamless integration with external data sources, the BeachRecs system ensures efficient, reliable, and proactive coastal safety management. This design not only enhances user experience but also significantly contributes to reducing risks associated with coastal tourism through timely and informed decision-making.

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IV. SIMULATION DETAILS

➢ *Data Acquisition and Integration Layer*

The data acquisition and integration layer forms the foundation of the proposed system by enabling the collection and consolidation of real-time as well as forecast-based environmental data from multiple trusted sources. This multi-source integration ensures comprehensive situational awareness and improves the reliability of coastal safety assessment.

The system continuously collects structured environmental data through the integration of multiple external Application Programming Interfaces (APIs). Real-time weather parameters, including temperature, wind speed, humidity, and storm alerts, are obtained using the OpenWeather API. Tidal information, such as sea level height, tidal predictions, and hourly tide schedules, is acquired from the NOAA Tide Data API. Additionally, the Google Maps API is utilized to obtain geospatial information, including beach location coordinates, nearby amenities, and route optimization for navigation. These APIs are accessed using REST-based HTTP requests at predefined intervals. The retrieved data is validated, parsed into structured JSON format, and time-stamped before being stored in the cloud database. This multi-source integration approach ensures the availability of high-quality, heterogeneous data required for accurate machine learning-based prediction.

All collected data is managed using a cloud-based infrastructure built on a real-time database, such as Google Firebase. This platform provides low-latency data synchronization, automatic scalability, fault tolerance, and secure authentication mechanisms. The data is categorized into static data (beach metadata and location information), dynamic data (weather and tidal parameters), and user-generated data (reviews and reports). The cloud-based architecture enables seamless communication between backend processing modules and frontend applications, supporting real-time updates and efficient data retrieval for predictive analytics.

➢ *Processing and Intelligence Layer*

The processing and intelligence layer is responsible for transforming raw environmental data into meaningful insights through preprocessing, feature engineering, and machine learning-based safety evaluation. This layer plays a critical role in ensuring accurate and reliable prediction of beach safety conditions.

Initially, the collected raw data undergoes preprocessing to ensure consistency and quality. This includes outlier detection to eliminate anomalous values, particularly in parameters such as wave height, normalization of heterogeneous features such as latitude and longitude, and temporal alignment of datasets obtained from multiple APIs. These preprocessing steps improve data consistency and enhance the robustness of the predictive model.

Subsequently, feature extraction is performed to identify key environmental attributes relevant to safety assessment. Important features include wind speed, wave height, temperature, and ultraviolet (UV) index. In addition to these primary features, derived parameters such as storm risk score and tidal hazard factor are computed to enhance predictive performance. These engineered features enable the model to better capture complex environmental relationships and improve classification accuracy.

For safety prediction, the system employs an Extreme Gradient Boosting (XGBoost) classifier, which is a powerful ensemble learning method based on gradient boosting decision trees. XGBoost is selected due to its ability to effectively handle non-linear relationships, heterogeneous data types, and feature interactions commonly present in environmental datasets. The model iteratively constructs decision trees by minimizing a regularized objective function, thereby improving prediction accuracy while preventing overfitting. Using the extracted features, the XGBoost model computes the Beach Safety Index, categorizing each coastal location into three classes: safe (green), moderate risk (orange), and dangerous (red).

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Text heads organize the topics on a relational, hierarchical basis. For example, the paper title is the primary text head because all subsequent material relates and elaborates on this one topic. If there are two or more sub-topics, the next level head (uppercase Roman numerals) should be used and, conversely, if there are not at least two sub-topics, then no subheads should be introduced. Styles named "Heading 1," "Heading 2," "Heading 3," and "Heading 4" are prescribed.

➢ *Figures and Tables*

- *Positioning Figures and Tables:*

Place figures and tables at the top and bottom of columns. Avoid placing them in the middle of columns. Large figures and tables may span across both columns. Figure captions should be below the figures; table heads should appear above the tables. Insert figures and tables after they are cited in the text. Use the abbreviation "Fig. 1," even at the beginning of a sentence.

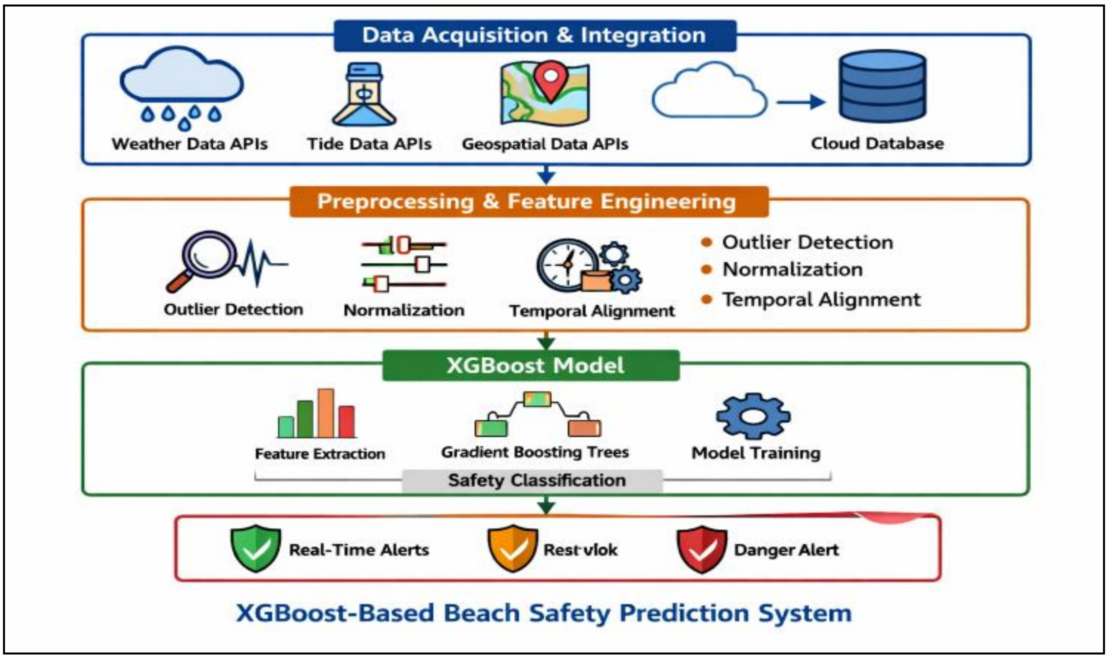

Fig 2 XGBoost-Based Beach Safety Prediction System

The overall workflow of the system involves a sequence of operations starting from API-based data collection, followed by data validation and storage in the cloud. The data is then pre-processed and transformed through feature engineering, after which the XGBoost model performs real-time safety prediction. The computed safety index is delivered to the user interface through dynamic visualization and alert mechanisms, enabling users to make informed decisions.

➢ *Dataset Description*

The dataset utilized in this study consists of coastal environmental parameters collected from multiple geographical locations, incorporating both spatial and temporal attributes required for safety prediction.

The dataset includes features such as latitude and longitude, which define the geographical position of beaches, wave height representing sea conditions in meters, and timestamp information recorded in Coordinated Universal Time (UTC). Additional environmental parameters such as wind speed and temperature are also incorporated to improve model performance. The target variable is defined as a safety label, categorized into three classes: safe (green), moderate (orange), and dangerous (red). Prior to model training, the dataset undergoes preprocessing to extract meaningful temporal features from the timestamp. The UTC time is transformed into structured attributes such as hour, day, and month, enabling the model to capture temporal variations in environmental conditions. This transformation enhances the ability of the XGBoost model to learn time-dependent patterns associated with coastal hazards. For evaluation, the dataset is divided into training and testing subsets using an 80:20 ratio. The training set is used to train the XGBoost classifier, while the testing set is used to evaluate its performance in terms of accuracy and generalization. The experimental results demonstrate that the XGBoost-based approach provides reliable and efficient prediction of coastal safety conditions.

V. RESULTS AND DISCUSSION

Fig. 3 illustrates the variation of the training loss with respect to the number of epochs during the learning process. The loss curve demonstrates a clear decreasing trend, indicating that the model is effectively learning from the training data and minimizing the prediction error over successive iterations. In the initial epochs, a relatively higher loss value is observed, which is expected as the model parameters are randomly initialized and have not yet adapted to the underlying data patterns. As the number of epochs increases, the loss gradually decreases, reflecting improved model performance and better convergence behaviour. Furthermore, the curve shows a smooth and stable decline without significant fluctuations, which suggests that the training process is well-optimized and free from issues such as instability or divergence. Towards the later epochs, the loss values tend to plateau, indicating that the model has reached a near-optimal solution and additional training yields only marginal improvements. This behaviour confirms that the selected model configuration and learning parameters are appropriate for the given dataset. Overall, the loss curve validates the effectiveness of the training process and demonstrates the capability of the proposed model to achieve reliable and consistent performance.

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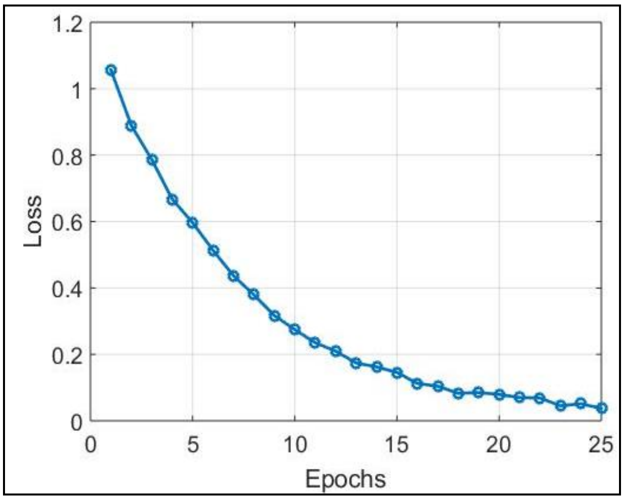

Fig 3 Loss vs. Epochs

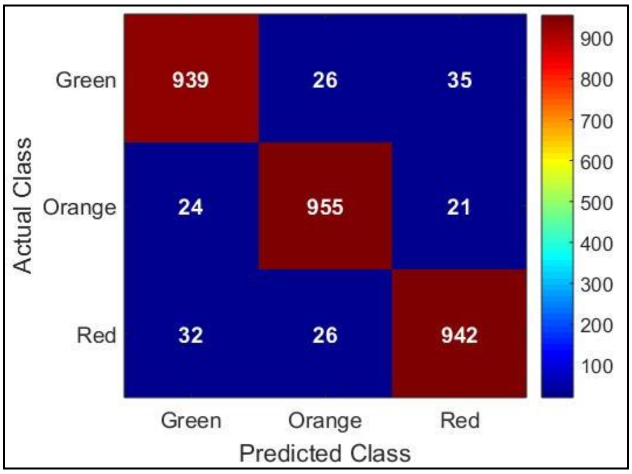

Fig 4 Confusion Matrix

Fig. 4 presents the confusion matrix of the proposed classification model, illustrating the performance of the system in correctly predicting the three safety classes: Green (Safe), Orange (Moderate Risk), and Red (Danger). The matrix provides a detailed comparison between the actual class labels and the predicted outputs, enabling a comprehensive evaluation of classification accuracy and error distribution.

It can be observed that the majority of the samples are concentrated along the diagonal elements of the matrix, indicating a high number of correct classifications for all three classes. The Green class shows strong prediction accuracy with minimal misclassification into orange or red categories. Similarly, the orange class demonstrates slightly higher recall, with most instances correctly identified, while only a few are misclassified. The Red class also exhibits high precision and recall, confirming the model's effectiveness in identifying high-risk conditions accurately.

The off-diagonal elements represent misclassifications, which are relatively small in number, thereby validating the robustness of the model. These minor errors may arise due to overlapping environmental conditions between adjacent safety levels. Overall, the confusion matrix confirms that the proposed model achieves high classification performance with an overall accuracy of approximately 94.53%, and maintains balanced precision and recall across all classes, making it suitable for reliable real-time coastal safety prediction.

Table 1 Classification Performance Metrics

Class	Precision	Recall	F1-Score
Green	0.944	0.939	0.941
Orange	0.948	0.955	0.952
Red	0.944	0.942	0.943

The classification performance metrics for the three classes are as follows. The Green class achieved a precision of 0.944, a recall of 0.939, and an F1-score of 0.941. The Orange class showed slightly higher performance, with a precision of 0.948, a recall of 0.955, and an F1-score of 0.952. The Red class recorded a precision of 0.944, a recall of 0.942, and an F1-score of 0.943. Overall, the results indicate consistently high performance across all classes.

VI. CONCLUSION

BeachRecs-India represents a significant advancement in the field of Smart Tourism by leveraging Artificial Intelligence (AI) and Machine Learning (ML) to enhance beach safety in India. The developed Smart Mobile and Web Application provides a holistic and scalable solution, delivering hyper-local, actionable insights based on pre-processed tidal and weather data rather than real-time streams. The project demonstrates that the strategic integration of technology—specifically the generation of a Beach Safety Index from complex tidal and weather data using APIs such as OpenWeather—can meaningfully improve the safety and overall experience for tourists. The classification system achieved consistently high performance, with the Green class recording a precision of 0.944, recall of 0.939, and F1-score of 0.941; the Orange class achieving a precision of 0.948, recall of 0.955, and F1-score of 0.952; and the Red class showing a precision of 0.944, recall of 0.942, and F1-score of 0.943. These results indicate reliable and accurate beach safety predictions from the non-real-time data.

Future work will focus on global expansion, the integration of more advanced Natural Language Processing (NLP) for the embedded chatbot, and exploring optional support for Wearable Devices (WD) for non-continuous health and safety notifications. These enhancements will further strengthen BeachRecs as a leader in digital beach safety platforms while maintaining a robust, pre-processed data-driven approach.

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