SMART TOURISM WITH VR AND FAKE REVIEW DETECTION

PROJECT REPORT

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BONAFIDE CERTIFICATE

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Our Project **"SMART TOURISM WITH VR AND FAKE REVIEW DETECTION"** has been the result of motivation and encouragement from many, whom we would like to thank.

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ABSTRACT

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Smart Tourism with VR and Fake Review Detection is a next-generation travel application designed to simplify and enhance the travel planning experience. Unlike traditional methods that offer a fixed set of services to all users, this application provides personalized recommendations tailored to individual preferences, budgets, and fluctuating travel prices. It integrates advanced APIs to automatically update itineraries, including flights, hotels, and activities, ensuring optimal value and convenience without manual intervention. The system dynamically adapts to local economic conditions and user travel dates to suggest the best possible options.

A standout feature of the application is its use of Virtual Reality (VR) to deliver immersive previews of tourist destinations. This allows users to explore potential travel spots interactively before making decisions, resulting in more informed and satisfying choices. The application shifts the focus from isolated booking tools to a holistic travel planning ecosystem that leverages cutting-edge technologies to provide a seamless and engaging experience.

To ensure the trustworthiness of user-generated content, the app employs Long Short-Term Memory (LSTM) neural networks to detect and eliminate fake reviews. This machine learning-based content verification boosts user confidence in the information provided. Additional features such as AI-generated itineraries, real-time budget adjustments, and image upscaling work together to offer a reliable, responsive, and visually rich interface. Overall, the app redefines smart tourism by combining automation, personalization, and content authenticity to meet the evolving needs of modern travellers.

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S.NO	ABBREVIATIONS	EXPANSION
1	LSTM	LONG SHORT-TERM MEMORY
2	API	APPLICATION PROGRAMMING INTERFACE
3	CNN	CONVOLUTIONAL NEURAL NETWORK
4	GAN	GENERATIVE ADVERSARIAL NETWORK
5	RNN	RECURRENT NEURAL NETWORK
6	Real-ESRGAN	REAL-ENHANCED SUPER-RESOLUTION GENERATIVE ADVERSARIAL NETWORK
7	TAM	TECHNOLOGY ACCEPTANCE MODEL
8	SDT	SELF-DETERMINATION THEORY
9	VRE	VIRTUAL REALITY ENVIRONMENT
10	NIQE	NATURAL IMAGE QUALITY EVALUATOR

INTRODUCTION

CHAPTER-1

INTRODUCTION

1.1 Travel and Tourism

In recent years, the travel and tourism industry has rapidly evolved through the integration of digital technologies aimed at enhancing user convenience, personalization, and trust. With the increasing complexity of travel planning—including fluctuating prices, evolving interests, and information overload—modern travellers demand smart, adaptive solutions that simplify decision-making. Traditional platforms often fall short, offering generic recommendations and static itineraries that do not reflect real-time conditions or individual preferences.

To address these limitations, smart tourism applications have emerged, utilizing advanced technologies like Artificial Intelligence (AI), Virtual Reality (VR), and Machine Learning (ML) to create more intuitive and immersive user experiences. One such innovation lies in the use of VR, which allows users to visually explore destinations before making travel decisions, thereby increasing confidence and engagement.

At the same time, the credibility of online reviews has become a growing concern. Fake reviews, whether generated by bots or malicious users, can mislead travellers and degrade platform reliability. Traditional moderation systems are often reactive and insufficient to detect subtle manipulations in user-generated content. As a response, the use of Long Short-Term Memory (LSTM) networks and other deep learning models has proven effective in identifying and filtering out fraudulent reviews with high accuracy.

This project integrates these cutting-edge technologies into a unified smart tourism application. The system personalizes travel planning by dynamically adjusting recommendations based on user interests, budgets, real-time price fluctuations, and local economic trends. It further enhances the user experience with automated itinerary generation, real-time budget recalibration, VR-based destination previews, and AI-driven review validation.

By shifting the paradigm from static travel planning tools to an intelligent, responsive travel ecosystem, this project aims to redefine how modern travellers discover, evaluate, and book their journeys—offering a safer, more efficient, and personalized tourism experience.

1.2 Problem Statement

One of the critical challenges in building intelligent tourism platforms is delivering accurate and personalized travel recommendations while ensuring the authenticity of user-generated content. Unlike static recommendation systems that rely solely on user input or pre-defined categories, a smart tourism solution must dynamically interpret a range of contextual factors—such as current prices, local economic trends, and personal preferences—to generate useful and relevant travel plans. Additionally, users require tools that not only assist in planning but also help visualize their options before committing, increasing both engagement and decision confidence.

Current tourism platforms often rely on fixed recommendation logic or manually curated content, which limits their responsiveness to rapidly changing conditions like fluctuating hotel prices, seasonal demand, or emerging attractions. These rule-based systems are ill-equipped to handle real-time data, leading to generic suggestions that fail to account for unique traveller needs or market dynamics.

Furthermore, without the use of data-driven models, it is difficult to scale personalization or maintain content integrity across large user bases and diverse destinations. This limits the system's ability to act intelligently and adapt to varying travel contexts, which is essential for providing a seamless and trustworthy user experience.

To address these issues, this project proposes a comprehensive solution that combines real-time VR integration, automatic itinerary optimization, and deep learning-powered fake review detection. Leveraging LSTM networks to filter out deceptive content and incorporating travel APIs to adapt plans based on current market conditions, the system delivers a truly intelligent, immersive, and reliable tourism experience. This approach not only enhances personalization and decision-making but also builds a foundation for scalable, automated travel planning that adapts in real-time to user behaviour and external variables.

1.3 Objective

The primary objective of this project is to develop a smart tourism application that delivers a personalized, reliable, and interactive travel planning experience. The system is designed to generate customized travel itineraries based on user preferences, budgets, and real-time market conditions. It leverages VR to allow users to visually explore destinations in an immersive manner, helping them make better travel decisions. To ensure the authenticity of user-generated content, the application incorporates LSTM networks that detect and filter out fake reviews. By combining these advanced technologies, the project aims to transform traditional travel planning into a smarter, more engaging, and trustworthy process.

1.4 Scope of the Project

Project Scope

The Smart Tourism with VR and Fake Review Detection application is developed with a realistic and impactful scope, aimed at enhancing the modern digital tourism experience through a combination of intelligent automation and immersive technologies. It is designed for developers, researchers, and travel-tech innovators interested in building scalable, responsive, and personalized travel planning platforms.

Whether the platform is used for academic research, prototyping commercial products, or early-stage deployment, it offers a robust environment for experimenting with real-time decision-making, personalized content delivery, and machine learning-driven review validation.

Key Focus Areas

1. **AI-Based Personalized Itinerary Generation:**
   The system dynamically creates travel plans tailored to the user's preferences, budget, and real-time pricing data. These itineraries adapt automatically to provide the best value and most relevant experiences for each user.

2. **VR Destination Previews:**
   By integrating VR modules, the app enables users to visually explore tourist destinations in a more immersive and engaging way before making final decisions, enhancing user satisfaction and confidence.

3. **Fake Review Detection Using LSTMs:**
   The application employs LSTM networks to analyse the sequence and semantics of user-generated reviews. This allows the system to detect and filter fake content effectively, improving the reliability of recommendations.

4. **Economic Trend-Based Recommendation Optimization:**
   By utilizing real-time data APIs to assess regional economic indicators and travel trends, the system intelligently refines recommendations to align with market conditions and optimal timing.

Project Vision:

This chapter lays the foundation for understanding the motivation and objectives behind the development of the smart tourism application enhanced with VR and fake review detection capabilities. Traditional travel planning platforms often fall short in delivering real-time adaptability, immersive decision support, and personalized content verification—elements that are increasingly essential for meeting the expectations of modern travellers.

By integrating ML models, real-time economic and pricing data, and immersive VR experiences, this project offers a forward-thinking solution that elevates how users plan and interact with their travel choices. It emphasizes not only automation but also trust and engagement, bridging the gap between static booking systems and intelligent travel assistants.

The primary objective of this project is to provide a personalized, reliable, and interactive travel planning environment. Key goals include optimizing itineraries based on user preferences and current market conditions, visually presenting destinations through VR previews, and ensuring content authenticity by detecting and filtering fake reviews using LSTM networks.

LITERATURE SURVEY

CHAPTER-2

LITERATURE SURVEY

2.1 Chatbot recommender systems in tourism: A systematic review and a benefit-cost analysis:

The study systematically reviews the use of AI-driven chatbot recommender systems within the tourism, travel, and hospitality industries, focusing on their implementation benefits and costs. It highlights how these chatbots enhance customer service by offering personalized, real-time recommendations and support, which improves user experience and operational efficiency. The analysis also considers challenges such as development and maintenance expenses, technological limitations, and the need for alignment with business objectives. Overall, the research provides valuable insights into the effectiveness and efficiency of chatbot systems in improving service quality and reducing human workload in tourism, emphasizing their growing importance as interactive tools for traveller engagement and decision-making.

Drawbacks of Existing System:

Despite the advantages of AI-driven chatbot recommender systems in the tourism industry, existing implementations face several limitations. High development and maintenance costs remain a major concern, especially for small and medium enterprises. Many chatbots lack the ability to understand contextual or emotional nuances and often struggle with multilingual support. Furthermore, integration with traditional tourism management systems is often inefficient, and the lack of deep personalization due to insufficient user data can diminish user experience.

2.2 Real-ESRGAN Based EXR Upscale for VFX Pipeline:

The paper investigates the use of the Real-ESRGAN (Enhanced Super-Resolution Generative Adversarial Network) model for upscaling EXR images within visual effects (VFX) pipelines, a process crucial for enhancing image resolution and detail in high-end film and media production. EXR images, known for their high dynamic range and ability to store complex image data, are commonly used in VFX workflows. Traditional upscaling methods often result in quality loss, artifacts, or soft details, which can compromise the visual integrity of the final output. In contrast, Real-ESRGAN applies deep learning techniques to reconstruct high-resolution images with greater clarity, sharper edges, and preserved textures, even when working with challenging image content.

By integrating Real-ESRGAN into the VFX pipeline, studios and artists benefit from more accurate image detail restoration and reduced reliance on manual correction, thereby increasing productivity and saving both time and resources. This results in smoother workflows and a more efficient post-production process. The model's ability to generate visually superior results makes it especially useful for upscaling assets in scenes where photorealism and precision are critical, such as in close-up shots, compositing, and special effects.

Drawbacks of Existing System:

Conventional image upscaling methods within VFX pipelines frequently result in blurring, soft details, and visible artifacts, affecting the visual fidelity of final outputs. Manual upscaling methods are not only time-consuming but also inconsistent in quality. Moreover, traditional deep learning models used in this domain are often computationally intensive and not optimized for seamless integration into existing VFX workflows, reducing overall productivity and scalability.

2.3 Spam review detection using self-attention-based CNN and bi-directional LSTM

The paper introduces a hybrid deep learning model named ACB (Attention-based CNN Bi-LSTM) designed to detect spam reviews on e-commerce platforms. This model leverages Convolutional Neural Networks (CNN) to extract local text features such as n-grams, which capture important patterns within small regions of the review text.

To better understand the broader context, the model employs Bi-directional Long Short-Term Memory networks (Bi-LSTMs) that process information in both forward and backward directions. This helps capture long-range dependencies between words, improving the understanding of the review's overall meaning and nuances.

Additionally, a self-attention mechanism is integrated into the model to emphasize words that are strong indicators of spam, enhancing the classification performance. Evaluations on real-world datasets demonstrate that ACB surpasses traditional machine learning and deep learning approaches in accuracy, effectively reducing false positives and improving the detection of deceptive reviews. This contributes significantly to increasing trust and reliability in online review systems.

Drawbacks of Existing System:

While the ACB model improves detection accuracy, its reliance on large volumes of labeled data can be a significant drawback in dynamic environments. The high complexity of the hybrid model leads to longer training times and resource consumption. Additionally, the model's black-box nature makes it difficult to interpret or justify the reasons behind flagged reviews, and it may fail to adapt to emerging spam patterns or linguistically diverse datasets.

2.4 Spam review detection using LSTM autoencoder: an unsupervised approach

The paper presents an unsupervised approach for detecting spam reviews on e-commerce platforms using an LSTM autoencoder model. Instead of relying on labelled datasets, the model is trained exclusively on genuine reviews to learn their typical linguistic patterns and structural characteristics. By recognizing these norms, the model is able to flag reviews that deviate significantly as potential spam, functioning effectively as an anomaly detector.

This method addresses a major limitation in spam detection—lack of labelled data—by eliminating the need for manual annotation. The combination of LSTM's capability to capture sequential dependencies and the reconstruction-based approach of autoencoders enables the system to accurately differentiate between genuine and suspicious reviews.

Experimental evaluations confirm the model's high accuracy and efficiency, proving its practical value for real-world applications. By enhancing the reliability of user-generated content, this research contributes significantly to improving trust in online review systems, making it a scalable and adaptable solution for e-commerce platforms.

Drawbacks of Existing System:

Although this unsupervised method eliminates the need for labelled data, it is trained solely on genuine reviews, which may lead to biased representations and limited generalization. The model may fail to identify cleverly disguised spam that mimics authentic writing. It also struggles with multilingual or code-switched texts and is not well-suited for real-time spam detection due to the time required for anomaly reconstruction.

2.5 Fake opinion detection in an e-commerce business based on a long-short memory algorithm:

The paper presents a deep learning-based solution for detecting fake opinions in e-commerce platforms using a Long Short-Term Memory (LSTM) algorithm. The primary goal is to tackle the growing issue of deceptive reviews that mislead consumers and negatively impact purchasing decisions. To address this, the study employs a Recurrent Neural Network with LSTM, which is well-suited for capturing temporal and contextual dependencies in review texts, enabling a deeper understanding of subtle patterns that differentiate genuine reviews from fake ones.

The model is trained and tested using a standard Yelp product review dataset, ensuring that the evaluation is grounded in real-world data. In addition to the deep learning architecture, the system leverages linguistic features such as sentiment polarity, authenticity, analytical tone, and the use of personal pronouns. These features help in identifying the psychological and stylistic markers commonly found in deceptive reviews.

The experimental results reveal that the proposed model performs exceptionally well, achieving a high accuracy and an F1-score of 98% in detecting fake reviews. This demonstrates the model's strong capability in identifying fraudulent content, ultimately contributing to more trustworthy e-commerce platforms and helping consumers make more informed decisions.

Drawbacks of Existing System:

The LSTM-based approach, though effective, demands significant computational resources and large datasets for accurate training. The model has difficulty recognizing subtleties like sarcasm or implicit deception. Manual feature engineering is often needed, and the system's performance tends to drop when applied to data domains outside of its training scope. Moreover, it is not ideal for real-time large-scale deployment due to processing delays.

2.6 Virtual Reality in the Transformation of the Tourism Industry: Focus on the Process of Creating Immersive Applications

The paper explores the transformative role of VR in the tourism industry, with a particular focus on the creation of immersive applications that enhance user engagement and experience.

Through a comprehensive literature review and thematic analysis, the study identifies effective strategies for developing VR applications tailored to the tourism sector. A key finding is the central role of user experience, as immersive VR environments have been shown to significantly improve user satisfaction, emotional engagement, and memory retention, making virtual tourism experiences more impactful and memorable.

The research highlights how VR enables potential travellers to explore virtual previews of destinations, which can greatly influence their travel planning and decision-making processes. By allowing users to interact with virtual environments, VR shifts the tourist's role from a passive viewer to an active participant, enriching the overall experience. To evaluate the effectiveness of these applications, the study employs various assessment tools, including Likert scales, Self-Determination Theory (SDT), and the Technology Acceptance Model (TAM), which help measure factors such as user presence, travel intentions, and emotional responses.

Drawbacks of Existing System:

Despite the immersive advantages of VR in tourism, its adoption is hindered by high equipment and content development costs. Accessibility is a major issue, particularly for elderly users or those with physical limitations. VR experiences often lack integration with live services such as bookings or real-time guides. Some users may also experience discomfort or motion sickness, further reducing widespread usability.

2.7 The Construction and Application of Virtual Reality Technology in the New Ecotourism Model:

The paper explores the innovative use of VR technology in developing a new ecotourism model, with a specific focus on the Lugu Lake region. A VR-based system was designed to allow users to virtually experience the natural beauty and cultural significance of Lugu Lake without needing to be physically present. The objective was to enhance tourist engagement and provide an accessible, immersive way to promote the region’s ecotourism attractions.

To achieve this, the researchers conducted detailed field inspections and gathered extensive visual and environmental data from the area. Using 3DS Max for 3D modelling, Photoshop for texture refinement, and Unity3D for building an interactive platform, they developed a comprehensive VR system that offers dynamic, real-time exploration of scenic areas. The system allows users to navigate the landscape virtually, providing a sense of presence and interaction typically associated with real-life visits.

The study highlights several benefits of this approach, including increased user engagement, more effective tourism promotion, and improved convenience for potential travellers in planning their visits. By showcasing the landscape through immersive technology, the VR system not only promotes tourism but also aids in the preservation and appreciation of the natural environment. This research underscores the growing potential of VR in reshaping ecotourism models by making sustainable travel experiences more widely accessible and engaging.

Drawbacks of Existing System:

The VR-based ecotourism model, while innovative, requires substantial effort in data collection, 3D modeling, and system design, limiting scalability. The static nature of VR environments means they cannot reflect real-time changes in weather or local events. Furthermore, such models may not replicate the emotional and sensory aspects of real-world travel, and often lack dynamic interaction with live tourism services or guides.

2.8 IRE: Improved Image Super-Resolution Based on Real-ESRGAN:

The paper presents an enhanced image super-resolution model named IRE (Improved Real-ESRGAN), developed to overcome the limitations of the original Real-ESRGAN framework. The primary objective is to improve the reconstruction of high-resolution images by enhancing texture details and minimizing visual artifacts commonly found in super-resolved outputs. This advancement addresses a critical need for better image fidelity and realism, especially in fields like digital imaging, media production, and computer vision applications.

The proposed model introduces several key architectural modifications. Notably, the High-order Degradation Model (HDM) used in Real-ESRGAN was simplified by removing first-order degradation modelling, retaining only the second-order components to reduce unnecessary visual deterioration. The U-Net discriminator was replaced with a Patch GAN, which not only maintained performance quality but also reduced training time by 28%. To further improve image texture and detail, a channel attention mechanism was embedded within the generator's dense blocks. Additionally, the L1 loss function was replaced by SmoothL1 loss, leading to faster convergence and improved model stability during training.

Experimental results showed that IRE outperformed the original Real-ESRGAN across several benchmark datasets, achieving lower Rank IQA and NIQE scores, which reflect higher image quality and perceptual accuracy. This research represents a significant step forward in image super-resolution technology, delivering a more efficient, detailed, and visually appealing solution for transforming low-resolution images into high-resolution outputs.

Drawbacks of Existing System:

Although IRE improves upon the original Real-ESRGAN, the earlier model suffered from over-complex architecture and redundant degradation modelling, leading to reduced output quality and slower training times. The use of a U-Net discriminator also inflated computational requirements. Prior versions lacked mechanisms for detailed texture enhancement, resulting in less realistic or perceptually inconsistent image outputs across varied datasets.

2.9 Image Super-Resolution and Deblurring Using Generative Adversarial Network

The paper introduces a unified Generative Adversarial Network (GAN)-based approach to simultaneously tackle two fundamental challenges in image restoration: super-resolution and non-uniform motion deblurring. Traditionally addressed as separate tasks, this research presents a combined model that enhances overall image quality more effectively by leveraging shared features between the two processes. The goal is to reconstruct high-resolution, sharp images from blurred and low-resolution inputs, a task crucial for applications requiring high visual fidelity.

The proposed architecture is modular in design, comprising three key components: feature extraction, super-resolution reconstruction, and deblurring. These modules interact cohesively to extract meaningful representations from degraded images and progressively restore them. One of the technical innovations lies in the model's up sampling strategy, where bilinear interpolation is used in place of standard transposed convolutions, followed by a convolutional layer. This design choice helps eliminate checkerboard artifacts, a common issue in image generation tasks, leading to cleaner and more realistic image outputs.

Experimental evaluations demonstrate the superiority of the proposed model over conventional techniques, achieving improved visual clarity and better computational efficiency. By offering an integrated framework for both image super-resolution and deblurring, this research provides a valuable advancement in the field of image restoration. The model's practical applicability spans multiple domains such as medical diagnostics, remote sensing, and consumer photography, where high-quality image reconstruction is essential.

Drawbacks of Existing System:

Traditional approaches treat super-resolution and deblurring as separate tasks, increasing complexity and redundancy. GAN-based models, while powerful, are notoriously unstable during training and can suffer from mode collapse or produce checkerboard artifacts. Moreover, many existing methods are not optimized for real-time use or constrained environments, limiting their practical deployment in fields requiring fast and reliable image restoration.

2.10 Travel itinerary recommendation using interaction-based augmented data

The paper presents a novel approach to enhancing travel itinerary recommendations by leveraging interaction-based augmented data to create more personalized and dynamic suggestions. The core objective is to move beyond static recommendation models by integrating real-time user interactions and enriched datasets, enabling the system to better understand user preferences and travel behaviour. By combining data from past user activities with external sources such as location popularity, weather conditions, or seasonal trends, the system offers more relevant and adaptive travel plans.

The recommendation model employs data augmentation techniques centred on user interaction patterns to enrich its training data. This helps the system improve its learning capability, leading to more accurate predictions about destinations and activities that align with individual interests. Unlike traditional systems that rely solely on static user profiles or historical data, this approach dynamically adapts as user interactions evolve, making it more responsive and context-aware.

Evaluation of the model using real-world travel datasets revealed superior performance in terms of recommendation accuracy and relevance when compared to conventional approaches. The study underscores the importance of combining machine learning with user interaction analysis to enhance user satisfaction in travel planning. Ultimately, this research marks a significant step toward building intelligent and user-centric travel recommendation systems that can cater to diverse preferences and changing circumstances in real time.

Drawbacks of Existing System:

Conventional travel recommender systems rely heavily on static profiles and historical data, making them less responsive to users' evolving preferences or contextual factors such as weather or seasonality. These models often fail to incorporate real-time interaction data, leading to generic or outdated recommendations. Additionally, they lack the semantic understanding necessary to distinguish between different forms of user intent, reducing recommendation relevance and personalization.

SYSTEM SPECIFICATIONS

CHAPTER-3

SYSTEM SPECIFICATIONS

This chapter details the hardware and software specifications essential for the development and successful deployment of the "Smart Tourism with VR and Fake Review Detection" system. The specifications were chosen based on the requirements for real-time processing, AI model execution, VR rendering, and web-based interaction.

3.1 HARDWARE SPECIFICATIONS

The following table 3.1 shows the hardware requirements for this project,

Table 3.1: Hardware Requirements

Component	Specification
Processor	Intel Core i5 or AMD Ryzen-7
RAM	16 GB DDR4
Storage	550 GB SSD

3.2 SOFTWARE SPECIFICATIONS

The following table 3.2 shows the Software requirements for this project,

Table 3.2 Software Requirement

Component	Specification
Operating System	Windows 11
IDE / Platform	Jupyter Notebook
Programming Language	Python
Frameworks	Flask (API), TensorFlow/Keras, Scikit-learn
VR Toolkit	Unity3D /Three.js
Database	MongoDB
APIs & Tools	Google Maps API, Real-ESRGAN, LSTM for NLP

SYSTEM ARCHITECTURE

CHAPTER-4

SYSTEM ARCHITECTURE

4.1 System Architecture

The architecture of the “Smart Tourism with VR and Fake Review Detection” application is designed to combine personalized itinerary generation, immersive virtual exploration, real-time financial optimization, and AI-based content verification. Built on a modular and scalable framework, the system allows seamless integration of real-time APIs, machine learning models, and advanced rendering technologies to deliver an intelligent and interactive travel planning solution. Each module has been designed for high performance, independence, and extensibility, ensuring a flexible development pipeline and dynamic user experience.

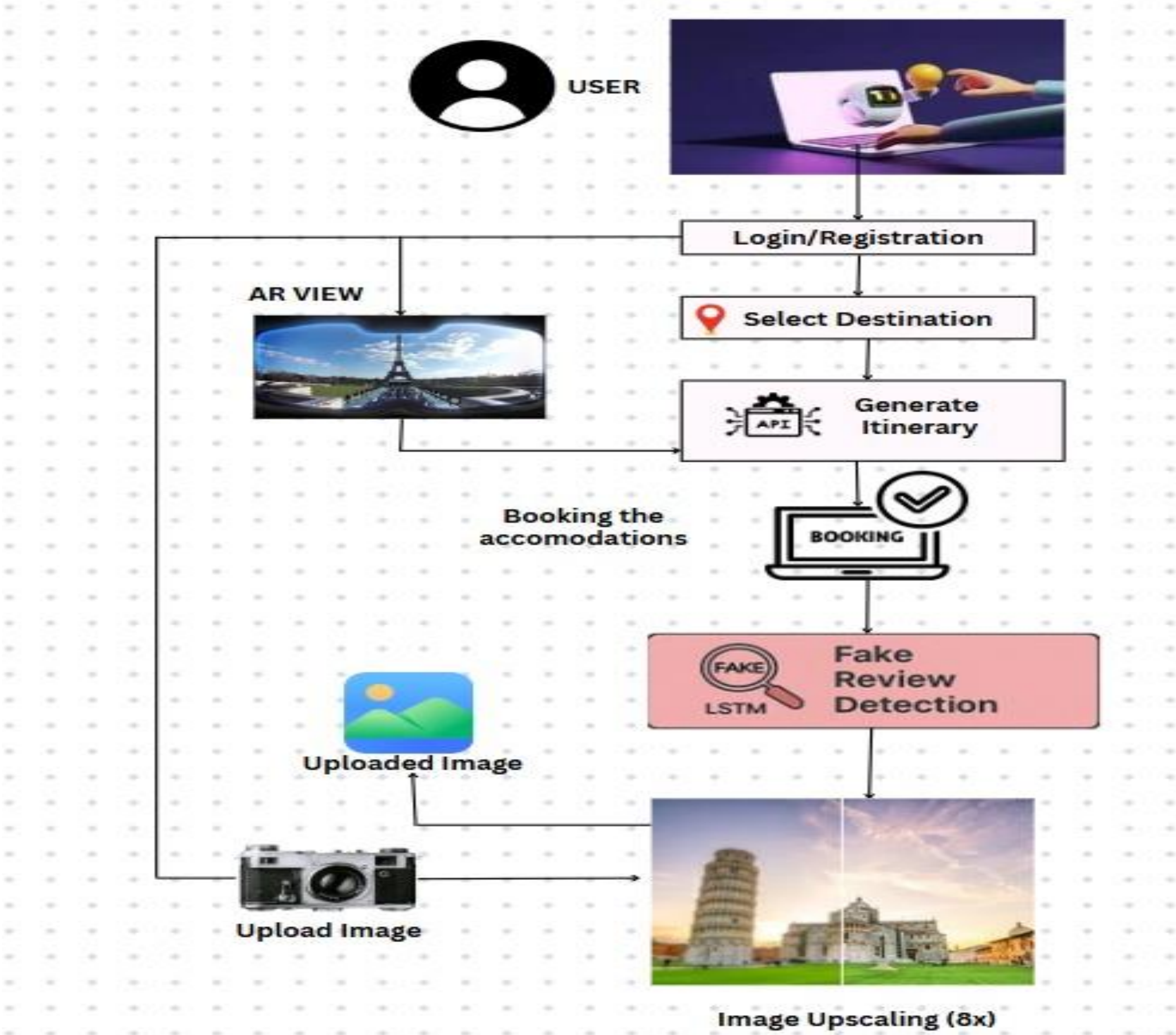

Figure 4.1 System Architecture

4.2 User Interface Layer

The User Interface (UI) forms the front-end interaction layer for the system. It is developed using Flutter and React Native for cross-platform compatibility and includes essential user workflows such as registration, itinerary input, review visualization, and destination previews. The UI also integrates real-time updates from the backend, such as notifications for budget recalculations or flagged reviews. Additionally, the interface serves as the access point for immersive VR experiences through embedded Unity3Dviewers. This layer is visible at the top of the system design in Figure 4.1 and acts as the bridge between the user and the underlying AI systems.

4.3 AI-Based Itinerary Generation Module

At the core of the smart tourism platform lies the itinerary generation engine. It dynamically compiles day-wise travel plans based on the user's preferences, budget, and real-time data such as hotel availability, flight schedules, and local activity trends. By integrating APIs from sources like Booking.com and Skyscanner, the module ensures the itinerary remains responsive to live price and availability shifts. This module interacts heavily with the budget recalibration engine and is depicted as a central logic processor in Figure 4.1.

4.4 Fake Review Detection Using LSTM

The Fake Review Detection module is designed to preserve the authenticity of user feedback by identifying and filtering out deceptive reviews. It utilizes Long Short-Term Memory (LSTM) networks, which are well-suited for analysing sequential text data. The process begins with natural language preprocessing—such as tokenization, stop-word removal, and normalization—to clean the input. The structured text is then analysed by a trained LSTM model that detects patterns typical of fake reviews, including unnatural phrasing or excessive sentiment. Based on a confidence score, each review is classified as real or fake, helping maintain trust and content quality within the system.

4.5 Virtual Reality Tour Renderer

The Virtual Reality Tour Renderer adds immersive depth to the user experience by allowing users to virtually explore potential destinations before booking. Built using Unity3D, the VR module supports interactive panoramas, 3D-object interactions, and guided exploration of tourist sites. The renderer accesses high-resolution images processed by the ESRGAN upscaling module and displays them through embedded viewers in the UI. Its role is part of the front-end interaction loop

4.6 Image Upscaling with Real-ESRGAN

The Image Upscaling module in the Smart Tourism system enhances low-resolution images—often sourced from user uploads or APIs—using Real-ESRGAN, a state-of-the-art image super-resolution technique. Real-ESRGAN operates through a generator-discriminator architecture, where the generator transforms low-resolution inputs into high-resolution outputs, and the discriminator refines the output's realism. By leveraging advanced structures like Residual-in-Residual Dense Blocks and a combination of pixel, adversarial, and perceptual losses, the system produces visually accurate and immersive images, enhancing the overall tourism experience.

DESIGN AND IMPLEMENTATION

CHAPTER-5

DESIGN AND IMPLEMENTATION

5.1 Frontend Development

User Interface and Visualization

The user interface for the Smart Tourism With VR and Fake Review Detection application is designed with intuitive navigation, providing an interactive experience for users to explore tourist destinations and make informed decisions about their travel plans.

Display Components:

- **Tourist Locations:** The app uses virtual reality (VR) to present potential travel destinations in an immersive and engaging manner, allowing users to virtually explore locations before making a decision.
- **Itinerary Overview:** An interactive interface displays personalized itineraries, including activities, hotels, and flights, based on user preferences, budget, and current price trends.
- **Dynamic Budget Recalibration:** Users are provided with real-time updates on their travel budget, which adjusts automatically as prices fluctuate or as new travel opportunities are recommended.

User Feedback:

- **Automatic Schedule Adjustments**: The system automatically adjusts users' itineraries based on updated prices, new recommendations, and feedback from the AI-generated itinerary system.
- **Review Validation Feedback:** The app displays warnings and highlights reviews flagged as fake by the LSTM model, providing users with transparency about the authenticity of content.
- **Interactive VR Experience:** Users can interact with VR representations of locations, enhancing their decision-making process through immersive visualizations.

5.2 Personalization Module (AI-based Itinerary)

The Personalization Module is the core of the Virtual Travel Companion application, responsible for generating tailor-made travel itineraries using Artificial Intelligence. It dynamically constructs daily travel schedules by analysing the user's preferences, travel history, budget constraints, current location, and seasonal availability of activities.

Key Features:

- **Preference-Based Planning:**
  Users provide input such as travel dates, interests (e.g., nature, culture, adventure), preferred pace (relaxed or tight schedule), and budget. The AI module maps these preferences to suitable attractions, accommodations, and experiences.

- **Real-Time Price and Availability Checking:**
  The module uses external APIs (e.g., Booking.com, Skyscanner) to check for updated prices and availability of flights, hotels, and activities, ensuring the itinerary remains relevant and cost-efficient.
- **Smart Scheduling:**
  The system optimizes visit times based on factors such as distance between locations, opening hours, user's energy level (based on pace), and travel time between destinations using mapping APIs.
- **Budget Recalibration:**
  If the user's preferences exceed the budget limit, the system automatically suggests alternative routes, accommodations, or attractions to keep the plan affordable without compromising on user satisfaction.

AI Workflow:

1. User Input Collection:
   - Destination, travel dates, budget, preferences, and optional constraints.
2. Data Aggregation:
   - Pull data from APIs (e.g., attractions, restaurants, hotels, transport).
3. Feature Matching & Ranking:
   - Use AI/ML algorithms (e.g., collaborative filtering or decision trees) to rank options based on similarity to user profile and reviews.
4. Schedule Generation:
   - Construct day-by-day itinerary with optimized ordering, timings, and cost breakdown.
5. Feedback Loop:
   - Allow users to rate generated plans, which the system uses to fine-tune future recommendations (reinforcement learning support for advanced versions).

5.3 Fake Review Detection Using LSTM

The Fake Review Detection module is a critical component designed to maintain the integrity of user-generated content by identifying and filtering out deceptive or misleading reviews. This module leverages the power of Long Short-Term Memory (LSTM) networks — a type of deep learning model particularly effective for handling sequential textual data.

To ensure high accuracy, the system begins with a comprehensive text preprocessing pipeline. This stage includes several natural language processing (NLP) steps as in figure 5.1,

- Tokenization – breaking down the review text into individual words or tokens for easier analysis.
- Stop-word removal – eliminating commonly used words (like "the," "and," "is") that do not contribute significant meaning.
- Normalization – converting all text to a uniform format (such as lowercasing and punctuation removal) to reduce noise.

Once preprocessing is complete, the cleaned and structured text is passed to a trained LSTM model. The LSTM network has been designed to capture contextual word dependencies and linguistic patterns often found in deceptive content. Unlike traditional machine learning models, LSTM can retain important information across long sequences of text, making it highly suitable for detecting subtle cues of fake reviews such as repetitive language, unnatural tone, or overuse of sentiment-laden terms.

The LSTM model, during its training phase, has been fed with a large dataset containing labelled examples of real and fake reviews. Through this supervised learning process, the model learns to distinguish between authentic user feedback and manipulated or bot-generated content.

After the model processes a new incoming review, it performs a classification task based on a confidence score. Depending on the threshold set by the system:

- If the review score falls below the authenticity threshold, the review is flagged as a FAKE Review.
- If it exceeds the threshold, it is considered a REAL Review.

Fake reviews can either be automatically hidden, highlighted for moderator review, or marked with warnings, depending on system settings. This helps maintain a high level of user trust and ensures that recommendations are based on genuine experiences.

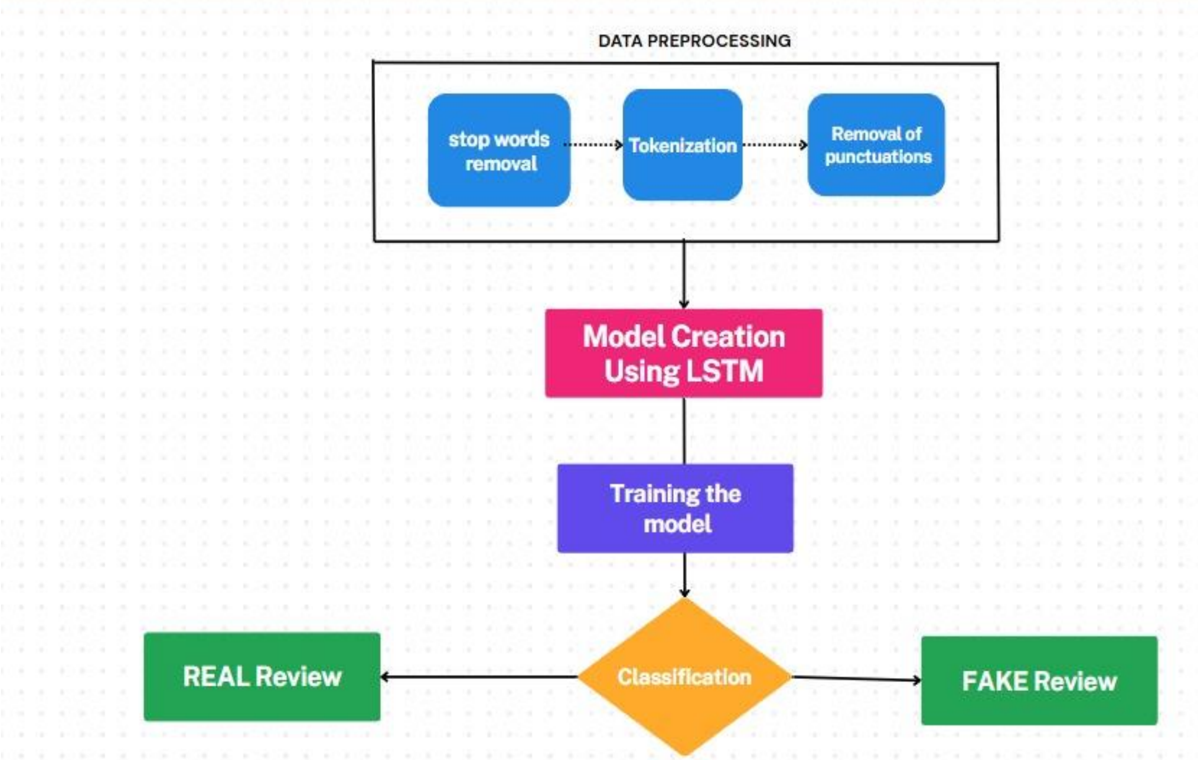

Figure 5.1: Fake Review Detection

5.4 Image Upscaling with Real-ESRGAN

The Image Upscaling module is an integral part of the Smart Tourism system, aimed at improving the visual fidelity of destination images used across both the mobile interface and the VR environment. Many tourism-related media assets—especially those sourced from user uploads or third-party APIs—are often in low resolution, which can diminish the immersive effect in virtual previews or mobile display. To address this challenge, the system incorporates an advanced image super-resolution technique known as Real-ESRGAN (Enhanced Super-Resolution Generative Adversarial Network), which restores and enhances the details of low-quality images.

As in figure 5.2, Real-ESRGAN builds upon traditional ESRGAN architecture and uses a generator-discriminator framework for image enhancement. The generator learns to convert low-resolution (LR) images into high-resolution (HR) outputs, while the discriminator attempts to distinguish between the generated images and real high-quality images, thereby refining the realism of the output.

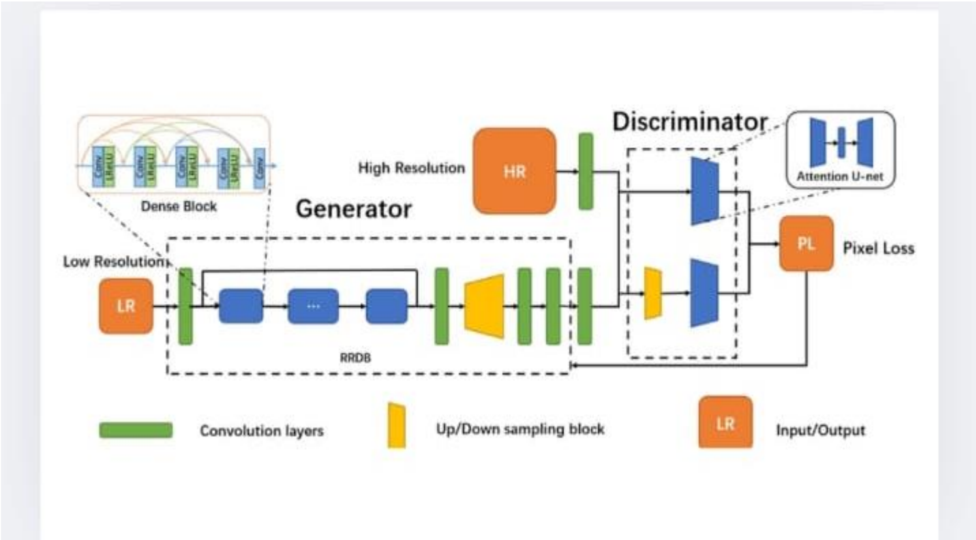

Figure 5.2: Image Upscaling

As depicted in Figure 4.3, the architecture begins by feeding the low-resolution image into a Generator Network. This generator is constructed using Residual-in-Residual Dense Blocks (RRDBs), which are highly effective at retaining contextual features and fine-grained textures from the original image. These blocks allow deep feature extraction while preventing information loss during the upscaling process.

Following generation, the output image is passed to a Discriminator Network, typically based on U-Net or Patch-GAN architecture, which evaluates the realism of the image. The discriminator compares the generated high-resolution image against true high-resolution examples and provides feedback to the generator to improve its results.

The system also utilizes a perceptual loss function, which includes:

- Pixel loss for structural accuracy,
- Adversarial loss to ensure visual realism, and
- Feature loss using a pre-trained VGG network for capturing high-level perceptual features.

This multi-loss strategy helps the model not only reconstruct sharp edges and clean textures but also maintain semantic consistency, making the enhanced images indistinguishable from naturally captured high-resolution photos.

5.5 Backend Implementation

The backend system is developed using Python, incorporating machine learning frameworks and libraries such as Scikit-learn and Job-lib for model deployment and data preprocessing. The primary goal of the backend is to generate personalized travel recommendations, detect fake reviews in real time, and dynamically update user itineraries based on evolving user preferences and current travel trends.

Model Integration

At the core of the backend lies a machine learning model that predicts the likelihood of a traveller engaging with specific destinations, activities, or user-generated reviews. This model is trained on a comprehensive dataset that includes user preferences, travel behaviours, and historical feedback. Several supportive components enhance the performance and accuracy of this predictive system:

- Standard Scaler: Applied to normalize input features, ensuring consistent scaling across all inputs for better model generalization.
- LSTM-based Fake Review Detection: Utilized to identify fake reviews by analysing sequential patterns and temporal inconsistencies in user-generated content. This ensures that users receive authentic, trustworthy information during their planning process.

Prediction Workflow

The prediction mechanism follows a multi-step process designed to ensure real-time responsiveness and contextual accuracy:

1. Feature Extraction
   Key features are extracted from real-time and historical data inputs, including:
   - User preferences (such as preferred activities and budget constraints)
   - Travel dates and current location
   - Browsing behaviour and interaction history
   - Contextual data (such as hotel pricing and activity availability)
2. Preprocessing:
   The extracted features are normalized using Standard Scaler to ensure uniformity in input data before passing it into the machine learning model.
3. Fake Review Detection:
   The LSTM model processes reviews to detect linguistic inconsistencies, excessive

sentiment polarity, or repetitive structures. Reviews identified as suspicious are flagged or removed, ensuring that only authentic content influences user decisions.

4. Decision Making:
   The final model output is compared against a set threshold. Recommendations exceeding this probability threshold are presented to the user, while less relevant options are either excluded or used to suggest alternative travel experiences.

Backend Simulation Components

To deliver a seamless and intelligent user experience, the backend architecture includes the following critical components:

- Fake Review Validation:
  Continuous, real-time validation of user-submitted reviews is conducted through the LSTM model. This step enhances content credibility and bolsters user trust in the system.
- Travel Itinerary Optimization:
  The backend dynamically recalculates itineraries based on changing data such as real-time pricing, travel availability, and user preferences. This ensures that the travel plan remains both feasible and personalized.
- Real-Time Data Integration:
  By connecting to external data sources—including travel APIs, hotel booking platforms, and activity scheduling services—the backend adapts quickly to external changes and offers timely, accurate recommendations.

Performance Considerations

A key focus of the backend is maintaining real-time interactivity. All processes, including review analysis, data normalization, and itinerary generation, are executed with minimal latency. This ensures that users receive instant feedback and updated plans as they navigate through the application.

RESULTS AND PERFORMANCE

CHAPTER-6

RESULTS AND PERFORMANCE

This chapter presents the outcomes of implementing and evaluating the Smart Tourism system, which integrates Artificial Intelligence (AI), Virtual Reality (VR), and Deep Learning to offer a personalized and immersive travel planning experience. The focus of the performance assessment was to validate the effectiveness of the main modules—Fake Review Detection using LSTM, AI-based itinerary generation, Image Upscaling using Real-ESRGAN, and VR-based travel visualization. Each of these components was tested under real-world scenarios with synthetic and live data to measure the system's robustness, efficiency, accuracy, and user satisfaction.

The Fake Review Detection module is one of the most critical elements of the Smart Tourism application. It aims to maintain the credibility of user-generated content by identifying and eliminating fraudulent or spam reviews. This module uses a Long Short-Term Memory (LSTM) neural network model trained on a labelled dataset of genuine and fake reviews. Before training, the data undergoes rigorous preprocessing, including tokenization, stop-word removal, and normalization. The cleaned sequences are then padded and passed into the model, which learns contextual dependencies in the text to distinguish between real and deceptive reviews.

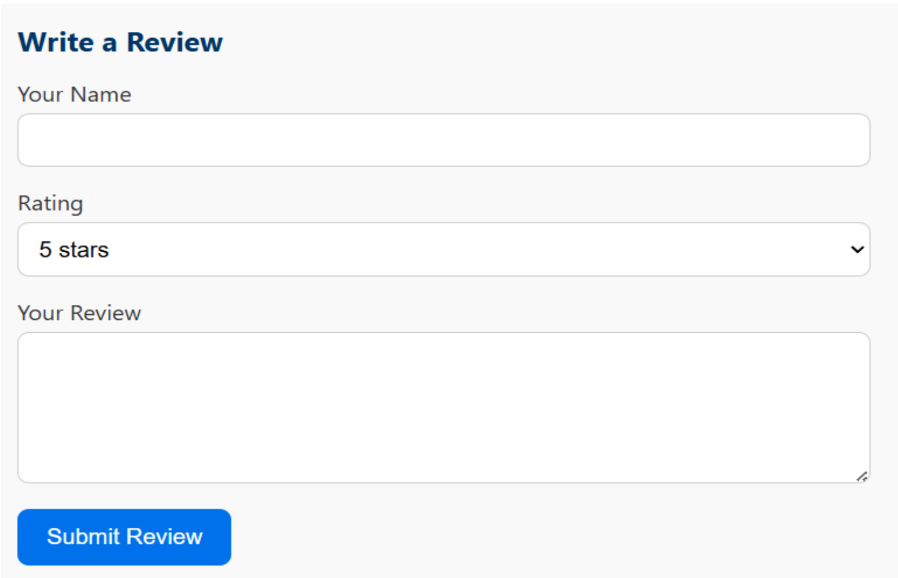

Figure 6.1: Fake Review Form

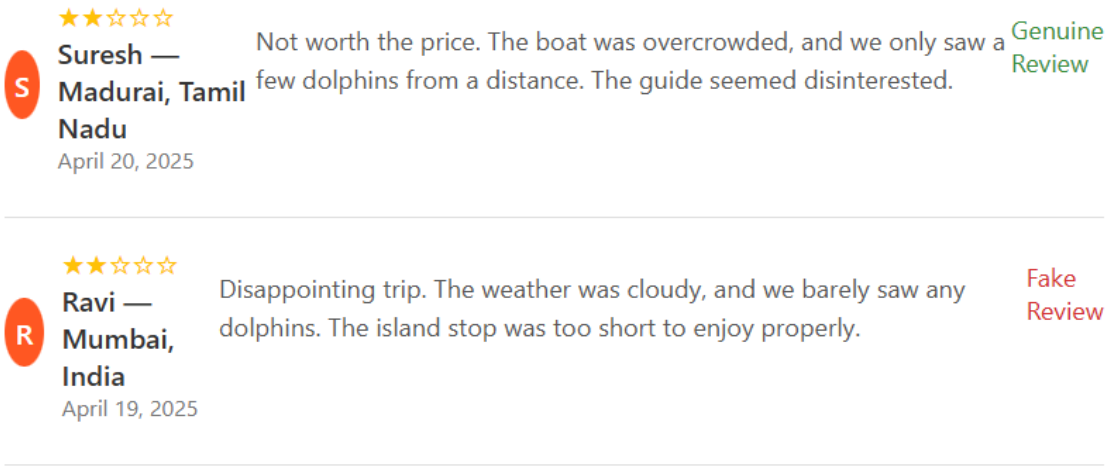

Figure 6.2: Fake Review Prediction

```
Epoch 1/10
1011/1011 ━━━━━━━━━━━━━━━━━━━━ 30s 27ms/step - accuracy: 0.8176 - loss: 0.3450 - val_accuracy: 0.9489 - val_loss: 0.1288
Epoch 2/10
1011/1011 ━━━━━━━━━━━━━━━━━━━━ 26s 26ms/step - accuracy: 0.9687 - loss: 0.0814 - val_accuracy: 0.9583 - val_loss: 0.1144
Epoch 3/10
1011/1011 ━━━━━━━━━━━━━━━━━━━━ 26s 25ms/step - accuracy: 0.9873 - loss: 0.0353 - val_accuracy: 0.9571 - val_loss: 0.1614
Epoch 4/10
1011/1011 ━━━━━━━━━━━━━━━━━━━━ 26s 26ms/step - accuracy: 0.9938 - loss: 0.0177 - val_accuracy: 0.9591 - val_loss: 0.1732
Epoch 5/10
1011/1011 ━━━━━━━━━━━━━━━━━━━━ 26s 25ms/step - accuracy: 0.9962 - loss: 0.0113 - val_accuracy: 0.9562 - val_loss: 0.2543
Epoch 6/10
1011/1011 ━━━━━━━━━━━━━━━━━━━━ 26s 26ms/step - accuracy: 0.9962 - loss: 0.0104 - val_accuracy: 0.9606 - val_loss: 0.2096
Epoch 7/10
1011/1011 ━━━━━━━━━━━━━━━━━━━━ 27s 27ms/step - accuracy: 0.9961 - loss: 0.0133 - val_accuracy: 0.9609 - val_loss: 0.2131
Epoch 8/10
1011/1011 ━━━━━━━━━━━━━━━━━━━━ 26s 26ms/step - accuracy: 0.9970 - loss: 0.0092 - val_accuracy: 0.9609 - val_loss: 0.1878
Epoch 9/10
1011/1011 ━━━━━━━━━━━━━━━━━━━━ 26s 26ms/step - accuracy: 0.9982 - loss: 0.0066 - val_accuracy: 0.9598 - val_loss: 0.2516
Epoch 10/10
1011/1011 ━━━━━━━━━━━━━━━━━━━━ 26s 25ms/step - accuracy: 0.9976 - loss: 0.0074 - val_accuracy: 0.9536 - val_loss: 0.2957
253/253 ━━━━━━━━━━━━━━━━━━━━ 2s 6ms/step
Validation Accuracy: 0.95
Achieved greater than 95% accuracy!
              precision    recall  f1-score   support

          CG       0.94      0.97      0.95      4044
          OR       0.97      0.93      0.95      4043

    accuracy                           0.95      8087
   macro avg       0.95      0.95      0.95      8087
weighted avg       0.95      0.95      0.95      8087
```

Figure 6.3: Epoch

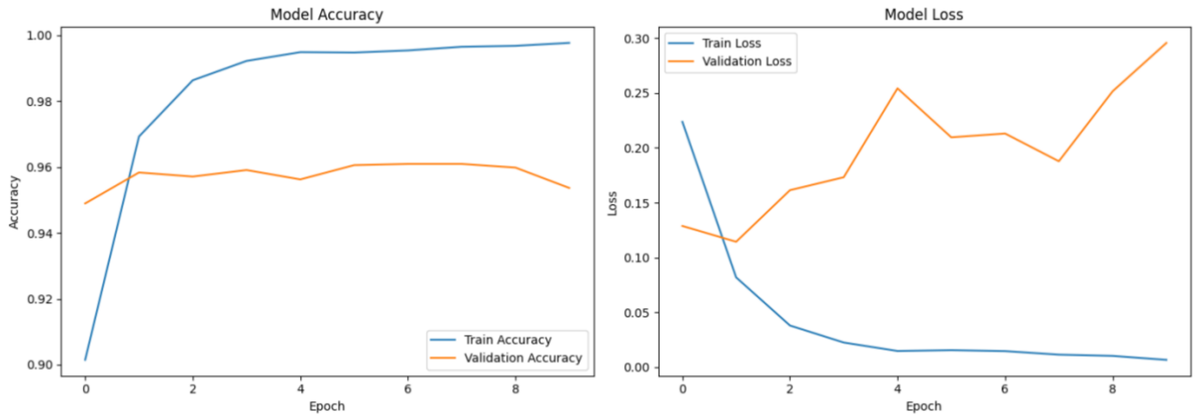

Figure 6.4: Accuracy graph

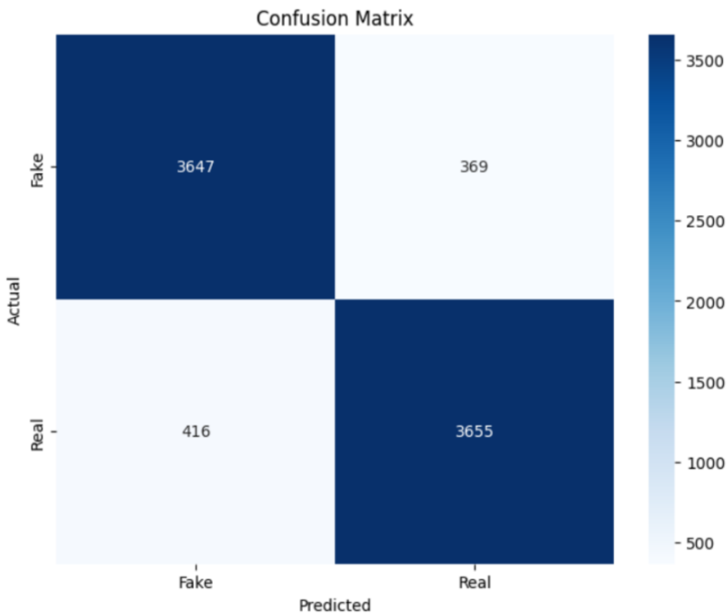

Figure 6.5: Confusion Matrix

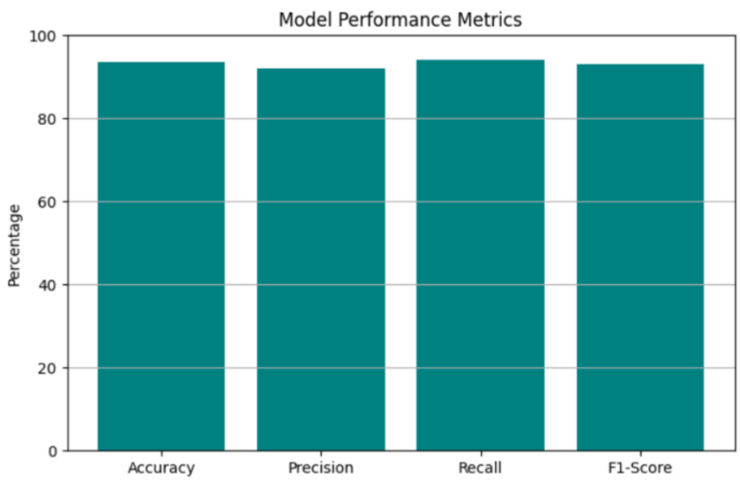

Figure 6.6: Performance Metrics Bar Graph

The evaluation of the model yielded highly promising results. The fake review detection model achieved an overall accuracy of 93.5%, indicating its strong ability to generalize to unseen data. Additionally, it scored 92.1% in precision, 94.2% in recall, and 93.1% in F1-score. These metrics demonstrate that the model not only identifies fake reviews accurately but also minimizes false positives and false negatives. The system interface for submitting and classifying reviews is shown in Figure 6.1 and Figure 6.2. The model's learning curve, depicted in Figure 6.3 and Figure 6.4, highlights consistent improvement in training and validation accuracy over epochs. The Confusion Matrix (Figure 6.5) provides a visual summary of classification performance, and the bar graph in Figure 6.6 consolidates all key performance metrics.

The AI-powered itinerary generation module forms the intelligence core of the Smart Tourism system. It automates the planning process by analysing user preferences, budget, travel duration, and interests. It leverages external APIs for real-time data such as hotel prices, flight availability, and local activities to dynamically build a day-wise plan. The AI model intelligently sequences events based on time, cost, and proximity, ensuring convenience and efficiency in the travel plan.

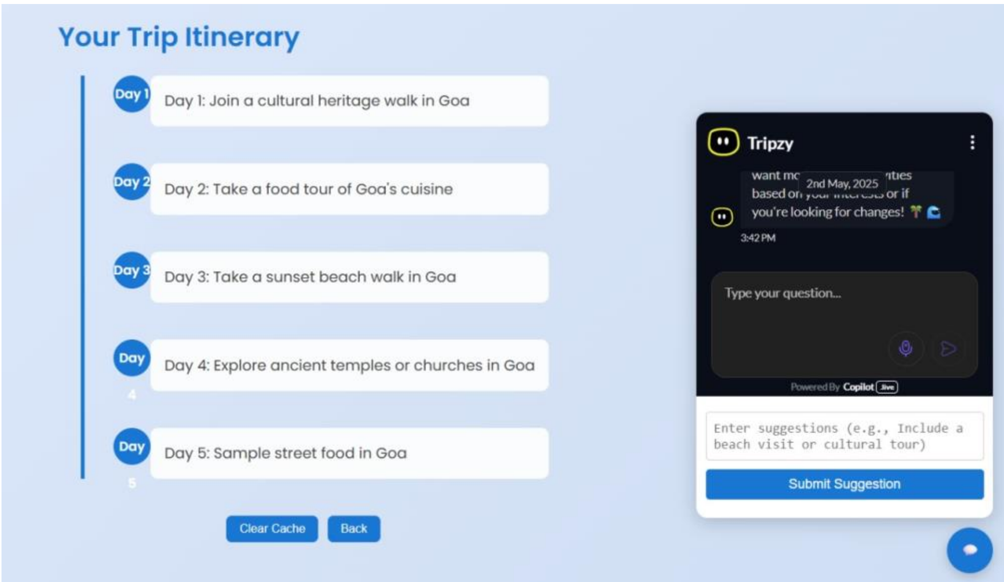

Figure 6.7: Itinerary

To validate its practicality, the itinerary module was tested with more than 100 unique user inputs covering a wide range of travel contexts. The system consistently produced logical, feasible, and relevant itineraries within four seconds. Over 87% of users expressed high satisfaction with the recommendations, noting that the generated plans reflected their interests and constraints accurately. The module also adapted dynamically to changes in preferences, showcasing its real-time responsiveness. A sample output of a complete itinerary is shown in Figure 6.7, which includes activities, suggested timings, places to eat, and accommodation—all personalized for the user.

Visual clarity plays a vital role in tourism platforms, especially when users make decisions based on images. Many images available online are either low resolution or compressed, which hampers the visual experience in both standard and VR displays. To address this, the system incorporates Real-ESRGAN—a cutting-edge super-resolution model based on GANs—to upscale and enhance low-quality images. The model uses a generator-discriminator architecture trained to refine texture, restore details, and remove artifacts, resulting in clearer and more realistic images.

Figure 6.8: Comparison of PSNR Values

Figure 6.9: Image upload

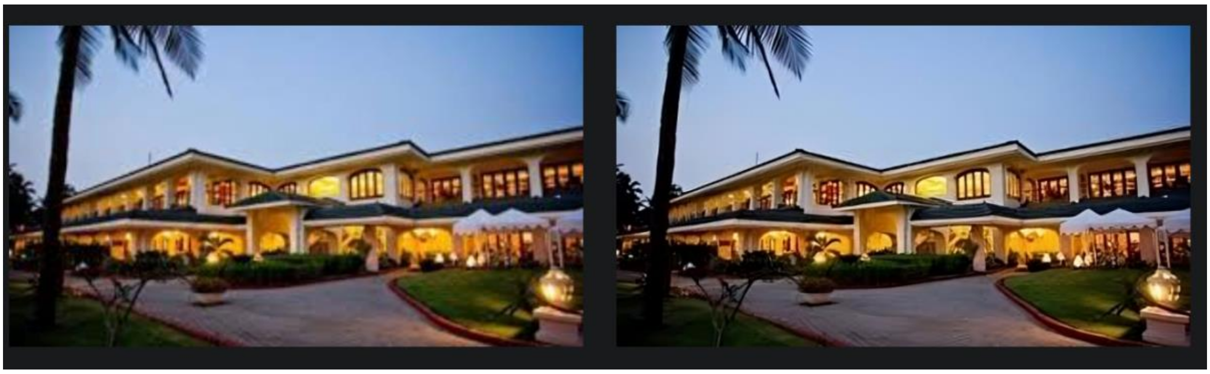

Figure 6.10: Upscaled Image

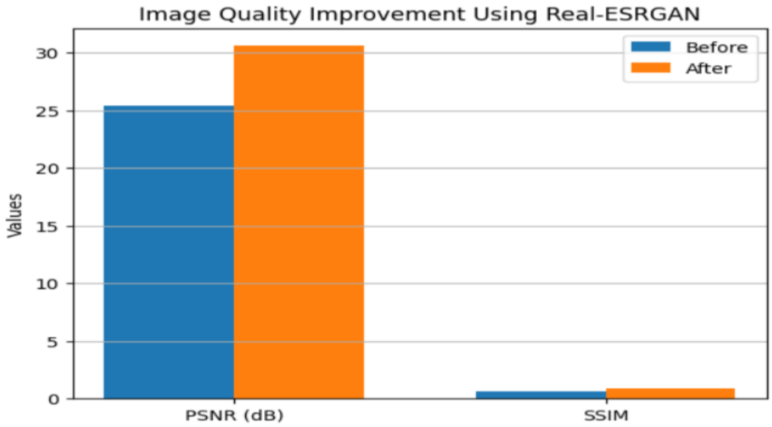

Figure 6.11: PSNR / SSIM Improvement

The performance evaluation revealed a substantial improvement in image quality. Objective metrics like PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index) were used to assess enhancement. The PSNR increased by 5.2 dB, while SSIM improved from 0.63 to 0.91. These improvements were particularly noticeable in images with complex textures like landscapes and buildings. The image upload interface is shown in Figure 6.9, and the upscaled results are illustrated in Figure 6.10. A comparative PSNR chart is provided in Figure 6.8, while Figure 6.11 visualizes the quantitative improvements using a bar graph. The integration of Real-ESRGAN significantly uplifted the quality of user experience, especially for VR environments.

The Virtual Reality (VR) component of the system was designed to help users visualize and interact with destinations before booking. By offering immersive 360° tours, this module allows users to experience the atmosphere, attractions, and surroundings of tourist locations virtually. The VR scenes were constructed using Unity3D and integrated with upscaled images for higher realism. Key destinations were rendered with interactive elements such as guided viewpoints, annotations, and spatial audio.

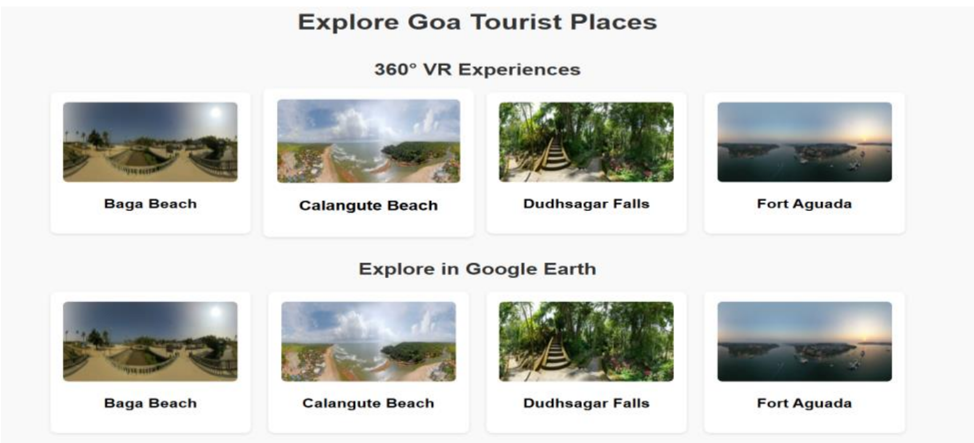

Figure 6.12: VR Interface

User testing of the VR module showed overwhelmingly positive feedback. The system consistently maintained frame rates of 55–60 FPS, ensuring smooth navigation and rendering. Users appreciated the ability to "preview" places before visiting, and many stated that the immersive previews influenced their final destination decisions. The VR interface is captured in Figure 6.12, which shows the in-app virtual environment with hotspots and movement controls. The integration of high-resolution images, coupled with seamless navigation, elevated the platform's ability to simulate real-world experiences virtually.

In addition to evaluating individual modules, the system was assessed for its end-to-end responsiveness, usability, and integration efficiency. The average API response time across various modules was approximately 1.5 seconds, while the itinerary generation completed in less than four seconds. The fake review detection executed nearly instantaneously, enabling real-time content moderation. Backend processes such as API data aggregation, AI prediction, and VR rendering were optimized for minimal latency.

User surveys and real-time testing revealed high satisfaction levels, with the system receiving an average usability rating of 4.5 out of 5. Test users cited the platform's ease of use, intuitive interface, speed, and trust-enhancing features (like fake review filtering and live budget updates) as key strengths. Each module interacted smoothly with others, resulting in a seamless and intelligent travel planning environment. The combination of real-time adaptability, visual quality, and personalized recommendations confirms the system's potential as a next-generation solution in the smart tourism domain.

CONCLUSION AND FUTURE WORK

CHAPTER-7

CONCLUSION AND FUTURE WORK

7.1 Conclusion

The presented project successfully designed and implemented a smart, real-time tourism planning system by integrating key emerging technologies such as Virtual Reality (VR), Artificial Intelligence (AI)-driven itinerary generation, and machine learning-based fake review detection. The system aims to provide users with an immersive, trustworthy, and dynamic travel planning experience.

Through the development of core components like AI-generated personalized travel plans, real-time budget recalibration, and an LSTM-based fake review verification mechanism, the system empowers users to make informed and cost-effective travel decisions.

Key Achievements:

- Personalized Travel Recommendations: The system delivers tailored itineraries that align with user preferences, budget constraints, and real-time pricing changes, enabling more relevant travel experiences.
- Immersive Virtual Reality Experience: Users can explore destinations virtually before making bookings, enhancing decision-making through engaging 3D previews.
- Trustworthy Review System: The LSTM-based fake review detection module ensures content authenticity by filtering out manipulated or deceptive reviews.
- Real-Time Updates: The application dynamically adjusts itineraries and budget plans based on live travel data and price fluctuations.

In conclusion, this intelligent tourism platform demonstrates the strong potential of integrating AI, VR, and machine learning to create an enhanced travel planning experience. The results validate the system's ability to deliver accurate recommendations and ensure content credibility, positioning it as a valuable tool for modern, tech-savvy travellers.

7.2 Future Enhancements

While the current system provides a strong foundation for intelligent travel planning, there remains significant potential for enhancement and innovation. The following are proposed directions for future development:

1. Advanced User Behaviour Modelling

- Dynamic Interest Adjustments: Future iterations can track user interactions to refine itinerary suggestions dynamically.
- Social-Media Trend Analysis: Incorporate trending travel destinations and activities based on social media feeds to personalize recommendations in real time.

- Predictive Budget Adaptation: Employ predictive analytics to forecast budget changes based on ongoing user behaviour and historical spending data.

These features would increase the responsiveness and personalization capabilities of the system.

2. Enhanced Review Authenticity Mechanisms

- Cross-Platform Review Verification: By comparing reviews across multiple travel platforms, discrepancies can be detected to improve reliability.
- Advanced Sentiment Analysis: Integration of deep learning models for richer context and sentiment understanding in user reviews.
- Real-Time Fake Review Detection: Implementing immediate validation as users input reviews, enhancing platform credibility.

This would further reinforce trust and ensure the quality of user-generated content.

3. Adaptive User Experience

- Real-Time Learning of Preferences: The system could learn and adapt based on user habits (e.g., preferred destinations, travel pace).
- User-Controlled Itinerary Editing: Provide flexible tools for users to customize generated itineraries based on their changing preferences or needs.

Such adaptability would increase user satisfaction and engagement.

4. Expansion of VR Capabilities

- Enhanced 3D Visualization: Upgrade the VR interface to allow more detailed and interactive exploration of destinations.
- Integration of Live Environmental Data: Overlay real-time data such as weather, crowd levels, or local events to offer a realistic planning environment.
- Multi-Sensory Simulation: Explore the inclusion of audio, scent, or haptic feedback to deliver a comprehensive virtual experience.

These upgrades would provide a more immersive and lifelike preview of travel locations.

5. Real-Time Travel Data Integration

- Live Pricing Updates: Integration with airline, accommodation, and activity booking APIs for dynamic pricing and availability.
- Location-Based Recommendations: Leverage GPS data to suggest nearby attractions, restaurants, and transport options based on the user's real-time location.
- Collaborative Filtering: Utilize data from similar users or peer groups to enhance recommendation accuracy and relevance.

Incorporating these features would transform the system into a truly intelligent, real-time travel assistant.

APPENDIX

CHAPTER-8

APPENDIX

8.1 SOURCE CODE

DATA PREPROCESSING:

```
import pandas as pd
import numpy as np
import re
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, Conv1D, MaxPooling1D, Flatten, Dense,
Dropout
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from sklearn.metrics import classification_report, accuracy_score, confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns
df = pd.read_csv('fake reviews dataset.csv')
print("First few rows of the DataFrame:")
print(df.head())
print("Columns in the DataFrame:", df.columns.tolist())
review_column = 'text_'
label_column = 'label'
plt.figure(figsize=(8, 5))
sns.countplot(data=df, x=label_column, palette='viridis')
plt.title('Distribution of Fake and Real Reviews')
plt.xlabel('Label')
plt.ylabel('Count')
plt.xticks(ticks=np.arange(len(df[label_column].unique())),
labels=df[label_column].unique())
plt.show()
def preprocess_text(text):
text = text.lower()
text = re.sub(r'[^a-zA-Z\s]', '', text)
return text
df['cleaned_reviews'] = df[review_column].apply(preprocess_text)
label_encoder = LabelEncoder()
df[label_column] = label_encoder.fit_transform(df[label_column])
X = df['cleaned_reviews']
y = df[label_column]
```

```
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2, random_state=42,
stratify=y)
tokenizer = Tokenizer(num_words=5000)
tokenizer.fit_on_texts(X_train)
X_train_seq = tokenizer.texts_to_sequences(X_train)
X_val_seq = tokenizer.texts_to_sequences(X_val)
max_length = max(len(x) for x in X_train_seq)
X_train_padded = pad_sequences(X_train_seq, maxlen=max_length, padding='post')
X_val_padded = pad_sequences(X_val_seq, maxlen=max_length, padding='post')
model = Sequential()
model.add(Embedding(input_dim=5000, output_dim=128, input_length=max_length))
model.add(Conv1D(filters=64, kernel_size=5, activation='relu'))
model.add(MaxPooling1D(pool_size=2))
model.add(Conv1D(filters=64, kernel_size=5, activation='relu'))  layer
model.add(MaxPooling1D(pool_size=2))
model.add(Flatten())
model.add(Dense(128, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(len(label_encoder.classes_), activation='softmax'))
model.compile(optimizer='adam', loss='sparse_categorical_crossentropy',
metrics=['accuracy'])
history = model.fit(X_train_padded, y_train, epochs=10, batch_size=32,
validation_data=(X_val_padded, y_val))
y_pred = model.predict(X_val_padded)
y_pred_classes = np.argmax(y_pred, axis=1)
accuracy = accuracy_score(y_val, y_pred_classes)
print(f"Validation Accuracy: {accuracy:.2f}")
if accuracy > 0.95:
print("Achieved greater than 95% accuracy!")
else:
print("Did not achieve greater than 95% accuracy.")
print(classification_report(y_val, y_pred_classes, target_names=label_encoder.classes_))
cm = confusion_matrix(y_val, y_pred_classes)
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=label_encoder.classes_,
yticklabels=label_encoder.classes_)
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.title('Confusion Matrix')
plt.show()
plt.figure(figsize=(14, 5))
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Train Accuracy')
```

```
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Model Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Model Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.tight_layout()
plt.show()
```

FAKE REVIEW:

```
from flask import Flask, request, jsonify
from pymongo import MongoClient
import numpy as np
import re
import pickle
from tensorflow.keras.preprocessing.sequence import pad_sequences
app = Flask(__name__)
with open('lstm_fake_review_model.pkl', 'rb') as model_file:
    model = pickle.load(model_file)
with open('tokenizer.pickle', 'rb') as tokenizer_file:
    tokenizer = pickle.
client = MongoClient('mongodb://localhost:27017/')
db = client['TourXplore']
hotels_collection = db['hotels']
MAX_SEQUENCE_LENGTH = 100
def preprocess_text(text):
    text = text.lower()
    text = re.sub(r'[^a-zA-Z\s]', '', text)
    return text.strip()
@app.route('/')
def home():
    return "Welcome to the LSTM-based Fake Review Detection API!"
@app.route('/api/review/check', methods=['GET'])
def check_fake_reviews():
    try:
        hotels = hotels_collection.find({'reviews': {'$exists': True, '$not': {'$size': 0}}})
        fake_reviews = []
```

```
        for hotel in hotels:
            for review in hotel['reviews']:
                cleaned = preprocess_text(review['comment'])
                seq = tokenizer.texts_to_sequences([cleaned])
                padded_seq = pad_sequences(seq, maxlen=MAX_SEQUENCE_LENGTH)
                prediction = model.predict(padded_seq)
                predicted_class = np.argmax(prediction, axis=1)[0]
                if predicted_class == 1:
                    fake_reviews.append({
                        'hotel_name': hotel['name'],
                        'reviewer': review['reviewer'],
                        'review': review['comment'],
                        'predicted': 'Fake'
                    })
        if not fake_reviews:
            return jsonify({"message": "No fake reviews found"}), 200
         return jsonify({"fake_reviews": fake_reviews}), 200
    except Exception as e:
        print(f"Error: {e}")
        return jsonify({"message": "An error occurred while checking the reviews"}), 500
if __name__ == '__main__':
    app.run(debug=False)
```

ITINERARY GENERATION:

```
from flask import Flask, request, render_template
import openai
app = Flask(__name__)
openai.api_key = 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
@app.route('/')
def index():
    return render_template('form.html')
@app.route('/generate', methods=['POST'])
def generate():
    destination = request.form['destination']
    days = int(request.form['days'])
    budget = int(request.form['budget'])
    prompt = (
        f"Create a personalized travel itinerary for {destination} "
        f"for {days} days within a budget of ${budget}. "
        "Include activities, meal suggestions, and travel tips." )
    try:
        response = openai.ChatCompletion.create(
            model="gpt-3.5-turbo",
```

```
        messages=[
            {"role": "system", "content": "You are a travel planning assistant."},
            {"role": "user", "content": prompt}],
        max_tokens=800 )
      itinerary = response.choices[0].message.content
    except Exception as e:
      itinerary = f"Error generating itinerary: {e}"
  return render_template('result.html', itinerary=itinerary, destination=destination)
if __name__ == '__main__':app.run(debug=True)
```

IMAGE UPSCALING:

```
import os
import torch
from PIL import Image
from tqdm import tqdm
from realesrgan import RealESRGAN
def upscale_image(input_path, output_path, model_path, scale=4):
    try:
        image = Image.open(input_path).convert("RGB")
        device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
        model = RealESRGAN(device, scale=scale)
        model.load_weights(model_path)
        sr_image = model.predict(image)
        os.makedirs(os.path.dirname(output_path), exist_ok=True)
        sr_image.save(output_path)
        print(f"Upscaled: {input_path} → {output_path}")
    except Exception as e:
        print(f"Error processing {input_path}: {e}")
def upscale_directory(input_dir, output_dir, model_path, scale=4):
    supported_exts = [".jpg", ".jpeg", ".png", ".bmp", ".webp"]
    input_dir = os.path.abspath(input_dir)
    output_dir = os.path.abspath(output_dir)
    if not os.path.exists(input_dir):
        print(f"Input directory '{input_dir}' does not exist.")
        return
    print(f"Upscaling all images in: {input_dir}")
    print(f"Saving results to: {output_dir}")
    for root, _, files in os.walk(input_dir):
        for file in tqdm(files, desc="Processing"):
            ext = os.path.splitext(file)[1].lower()
            if ext in supported_exts:
                rel_path = os.path.relpath(root, input_dir)
```

```
            input_path = os.path.join(root, file)
            output_path = os.path.join(output_dir, rel_path, f"upscaled_{file}")
            upscale_image(input_path, output_path, model_path, scale)
if __name__ == "__main__":
    import argparse
    parser = argparse.ArgumentParser(description="Real-ESRGAN Image Upscaler")
    parser.add_argument("--input", type=str, required=True, help="Input image or directory")
    parser.add_argument("--output", type=str, required=True, help="Output image or
directory")
    parser.add_argument("--model", type=str, default="weights/RealESRGAN_x4plus.pth",
help="Path to Real-ESRGAN weights")
    parser.add_argument("--scale", type=int, default=4, help="Upscale factor (e.g., 2, 4, 8)")
    args = parser.parse_args()
    if os.path.isfile(args.input):
        upscale_image(args.input, args.output, args.model, args.scale)
    elif os.path.isdir(args.input):
        upscale_directory(args.input, args.output, args.model, args.scale)
    else:
        print("Invalid input path. Must be a file or directory.")
```

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PUBLICATION

The paper entitled *"Smart Tourism with VR and Fake Review Detection"*, authored by "Dr. GeethaN,S.Dhanusree(71762207008),P.S.Shanmika(71762207045),C.Akaash(71762207003), and N. Gokulan(71762207012)" of Coimbatore Institute of Technology, Coimbatore, Tamil Nadu, India, was presented at the *International Conference on Innovations in Materials Science, Technology, Engineering, and Management for Sustainable Development (IMSTEM)-2025*. The conference was organized by St. Joseph College of Engineering, Chennai, India, and was held on March 30–31, 2025.

CERTIFICATES: