Project Report

on

Evaluation of Luxury Hotel Brands: An Image-Based Analysis

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SCHOOL OF COMPUTER ENGINEERING AND TECHNOLOGY

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of BTech.(Computer Science & Engineering) have completed their project titled "*Evaluation of Luxury Hotel Brands: An Image-Based Analysis*" and have submitted this Capstone Project Report towards fulfillment of the requirement for the Degree-Bachelor of Computer Science & Engineering (BTech-CSE) for the academic year 2022-2023.

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Abstract

The project aims to examine luxury hotel images shared on social media platforms to gain insights into the hotel attributes that influence consumer evaluations. With users increasingly relying on hotel photos before making bookings, this study focuses on analyzing visual data from TripAdvisor using deep learning techniques.

The project involves training five different deep Convolutional Neural Network (CNN) architectures, including one developed from scratch, to accurately classify images from a real dataset. By studying 9,251 consumer pictures, the research highlights the significant role of non-textual elements like images, which traditional research methods fail to effectively capture. Specifically, the study identifies the key attributes that have the greatest impact on consumers' experiences, such as the restaurant, bedroom, and bathroom within the hotel.

Furthermore, the study showcases the practical application of deep learning algorithms in monitoring social media platforms and understanding consumer perceptions of luxury hotels through visual data analysis. This valuable information can be leveraged to develop more effective brand management strategies for luxury hotel managers. Additionally, the insights gained from this research provide hotel owners with a better understanding of their key attractions and areas that require improvement.

By combining the analysis of luxury hotel images with advanced deep learning techniques, this project offers a fresh and unique perspective on enhancing the consumer evaluation of luxury hotel brands. The practical implications of these findings extend to the hospitality industry, allowing hotel managers to better grasp customer preferences and expectations, leading to improved brand management strategies and elevated guest experiences.

Chapter 1

1. Introduction

The increasing demand for luxury brands is adding complexity to the luxury marketplace, presenting new challenges for brand managers [1]. Success in brand management relies on understanding consumers' expectations and effectively responding to generate profitability [2]. Luxury hotel management has gained attention from scholars and practitioners in both brand management and tourism management literature, while social media monitoring offers insights into consumer behavior and brand engagement. Furthermore, user-provided photos on the Internet are becoming increasingly important in product evaluation [3]. In this context, brand managers in luxury hotel management face the task of capturing and leveraging their brand's essence to create meaningful connections with customers. In the digital age, social media platforms provide a powerful avenue for consumers to share experiences, opinions, and visual content, offering valuable insights into their evaluations of luxury hotel brands. This research project aims to explore the impact of user-generated photos on consumer evaluations of luxury hotel brands, utilizing advanced techniques in AI, ML, Deep Learning, Image Processing, and Computer Vision to analyze and interpret these visual cues. By comprehensively understanding the attributes that significantly influence consumer evaluations, brand managers can refine their strategies and deliver exceptional guest experiences, effectively positioning luxury hotel brands for success in a highly competitive market.

1.1. Problem Statement

In the luxury hotel industry, brand managers face the challenge of understanding and meeting consumer expectations to drive brand success and profitability. With the increasing importance of social media platforms and user-generated content, such as photos shared by tourists, there is a need to explore the impact of visual content on consumer evaluations of luxury hotel brands. Traditional research methods often rely on textual feedback and reviews, which may not fully capture the experiential and aesthetic aspects conveyed through visual content. Therefore, the problem at hand is to investigate the attributes that significantly influence consumer evaluations of luxury hotel brands based on user-provided photos and to develop a deep learning-based approach to analyze and interpret these visual cues. By addressing this problem, the study aims to bridge the gap in understanding the role of visual content in shaping consumer perceptions and provide valuable insights for brand managers to enhance their strategies and elevate guest experiences in the luxury hotel domain.

1.2. Domain of Project

This project operates within the domain of AI, ML, Deep Learning, Image Processing, and Computer Vision. The integration of these cutting-edge technologies enables a comprehensive analysis of user-generated photos in the luxury hotel domain. Artificial Intelligence techniques, such as Machine Learning and Deep Learning, provide the foundation for training models to classify and interpret visual data. By leveraging Deep Learning algorithms, specifically Convolutional Neural Networks (CNNs), the project can effectively extract features and patterns from images, enabling a more nuanced understanding of the visual content shared by users.

Image processing techniques play a crucial role in preprocessing and enhancing the quality of the visual data. These techniques encompass tasks such as image resizing, noise reduction, and color correction, ensuring optimal inputs for the subsequent analysis. Additionally, Computer Vision techniques are employed to perform tasks such as image recognition, object detection, and attribute extraction, further enriching the analysis of the user-provided photos.

The combination of AI, ML, Deep Learning, Image Processing, and Computer Vision in this project creates a powerful framework for unlocking insights from visual data and unraveling the relationship between user-generated photos and consumer evaluations of luxury hotel brands. Through the application of these technologies, the project aims to push the boundaries of traditional research methods and provide a more holistic understanding of the visual aspects that influence brand perception in the luxury hotel industry.

1.3. Aim of the project

The need for this project arises from the growing significance of visual content and user-generated photos in shaping consumer evaluations of luxury hotel brands. Traditional research methods often rely on textual feedback and reviews, overlooking the experiential and aesthetic dimensions conveyed through visual content. To address this gap, the aim of this project is to investigate and understand the attributes that significantly impact consumer evaluations of luxury hotel brands based on user-provided photos.

To achieve this aim, the project will employ a deep learning-based approach, leveraging AI, ML, Deep Learning, Image Processing, and Computer Vision techniques. The implementation of these advanced technologies will enable the analysis and interpretation of large volumes of visual data, facilitating a comprehensive understanding of the role and impact of visual content in the luxury hotel domain.

The project will begin with the collection of user-generated photos from platforms such as TripAdvisor, which serve as a valuable source of visual data related to luxury hotel experiences. These photos will be preprocessed using image processing techniques to enhance quality and standardize inputs for analysis. Next, deep learning models, specifically Convolutional Neural Networks (CNNs), will be trained to classify and interpret the visual attributes within the photos.

The application of the project extends to multiple areas. Firstly, it provides valuable insights to luxury hotel brand managers, enabling them to refine their brand management strategies based on a deeper understanding of the visual elements that influence consumer evaluations. By identifying the attributes that have the greatest impact on consumer experiences, brand managers can prioritize improvements and enhance guest satisfaction.

Secondly, the project has implications for monitoring social media platforms and understanding consumer perceptions of luxury hotels. The deep learning-based analysis of user-generated photos allows for a more nuanced understanding of consumer behavior and engagement with luxury hotel brands. This knowledge can be leveraged to develop targeted marketing campaigns, tailored promotions, and personalized experiences to better engage with consumers.

In summary, the project aims to address the need for a comprehensive understanding of the impact of user-generated photos on consumer evaluations of luxury hotel brands. By implementing AI, ML, Deep Learning, Image Processing, and Computer Vision techniques, it seeks to uncover the visual attributes that drive consumer perceptions, thereby enabling brand managers to refine their strategies, enhance guest experiences, and effectively engage with consumers in the digital era.

Chapter 2

2. Literature Survey

Previous studies have made efforts to explore the factors influencing consumer satisfaction with hotel brands using various research methods. Questionnaires have been commonly used to gather consumer feedback [4], while online rating systems and sentiment analysis have been employed to assess consumer sentiment [5]. Additionally, the impact of social media interactions on consumer perceptions has been examined [6].

Recent research has also highlighted the influence of destination images on tourists' behavior throughout their travel journey [7]. Images, in particular, have emerged as preferred content in online posts, offering a virtual glimpse into hotel features and enhancing attractiveness [8]. Social media platforms such as Instagram and Facebook play a significant role in branding destinations, allowing for the curation of specific visual representations through filters and digital effects [9].

Consequently, brand managers have integrated social media into their marketing strategies, recognizing its fundamental role in their campaigns [10]. The presence on platforms like Facebook enables firms to attract new customers through electronic word-of-mouth communication and engage with existing ones, serving as a direct channel for brand interactions [11]. Moreover, the utilization of fan pages on social media contributes to reputation building, increased awareness, and the dissemination of corporate identity [12][13][14].

Specialized tourism platforms like TripAdvisor and Booking have become crucial resources for travelers, providing access to a vast amount of online reviews to inform travel decisions. TripAdvisor, in particular, stands as the largest travel platform, hosting millions of reviews and pictures of hotels, restaurants, and attractions [15]. User-provided photos, shared on such platforms, allow tourists to showcase their meaningful tourism experiences and receive appreciation from others, including strangers [16]. Consequently, researchers have recognized the value of these user-generated photos as rich data sources for tourism research.

However, despite the growing interest in social media analytics and the utilization of user-provided photos in understanding travel patterns [17], the specific contribution of these photos to the communicative effect of online reviews remains understudied. How user-provided photos influence users' perception of review quality compared to textual cues and other user-generated content is yet to be empirically examined. Thus, there is a need to develop new approaches, particularly leveraging deep learning techniques in computer image processing, to effectively process and interpret these user-provided product photos. The application of deep learning in natural language processing and image processing holds great potential in addressing the challenges associated with user-generated content on the internet and gaining a deeper understanding of the information value of online reviews in the hospitality and tourism domain.

Sr. No.	Name of Publication	Objective	Approaches	Result	Research Gap
1	Evaluation of Luxury Hotel Brands: "An Image-Based Analysis"	To explore the factors that drive content creation behavior on social networking sites (SNSs) from a commitment perspective. The researchers aimed to investigate the effects of both affective and normative commitments on content creation behavior.	The researchers collected data through an online survey of 423 SNS users in China. They used structural equation modeling (SEM) to test their proposed model and hypotheses.	The results of the study suggest that both affective and normative commitments have a significant positive effect on content creation behavior on SNSs. Affective commitment, which is the emotional attachment to the SNS, was found to be the strongest predictor of content creation behavior.	• Limited scope of image analysis. • Regional differences in luxury hotel brand perception • Consumer preferences for luxury hotel brands • Methodological limitations of image-based analysis • Limited sample size
2	The role of self-construal in consumers' electronic word of mouth (eWOM) in social networking sites: A social cognitive approach.	To explore the role of self-construal in consumers' electronic word of mouth (eWOM) behavior on social networking sites. Specifically, the researchers aimed to investigate the impact of independent and interdependent self-construals on the formation of eWOM intentions, attitudes, and behaviors on SNSs.	Data collection through an online survey of 268 SNS users in South Korea. A social cognitive approach to develop and test their proposed model, which examined the relationships among self-construal, eWOM intentions, and behaviors. Analyzed the data using structural equation modeling (SEM).	Results indicate that both independent and interdependent self-construals have a significant effect on eWOM intentions, attitudes, and behaviors on SNSs. consumers with an independent self-construal were more likely to engage in eWOM behaviors on SNSs than those with an interdependent self-construal.	Limited research on the role of self-construal in eWOM behavior. Limited application of social cognitive theory to eWOM behavior. Limited research on the impact of social networking sites on eWOM behavior Limited research on the moderating effect of culture on the relationship between self-construal and eWOM behavior.

3.	Mediating roles of social presence and channel commitment.	To investigate the mediating role of social presence and channel commitment in the relationship between social media engagement and sports channel loyalty. to understand how social media engagement influences sports channel loyalty and to identify the underlying psychological processes that explain this relationship.	Data collection through an online survey of 321 sports fans in South Korea. Use of structural equation modeling (SEM) to test proposed model, which examined the relationships among social media engagement, social presence, channel commitment, and sports channel loyalty.	Social media engagement has a significant positive effect on sports channel loyalty, and this relationship is partially mediated by social presence and channel commitment. Social media engagement has a direct effect on sports channel loyalty.	• Need for more research on how social presence and channel commitment influence consumers' trust and satisfaction in online shopping. • Need for more research on how different types of online shopping channels (e.g., website, mobile app, social media platform) affect consumers' social presence and channel commitment.
4.	Investigating the ripple effect in virtual communities: An example of Facebook Fan Pages.	To investigate the ripple effect in virtual communities, specifically in the context of Facebook Fan Pages. To understand how user interactions on Fan Pages can create a ripple effect and influence the behavior of other users,	Data collection from 305 Facebook users who were fans of a specific Fan Page. Use of structural equation modeling to test the proposed model, which examined the relationships among user engagement, social norms, social influence, and the ripple effect.	User engagement has a significant positive effect on the ripple effect, and this relationship is partially mediated by social norms and social influence. social norms, which are the perceived expectations of others in the community, mediate the relationship between user engagement and social influence,	• Limited research on the ripple effect of virtual communities, especially in the context of Facebook Fan Pages. • Need for more research on how different types of content (e.g., text, images, videos) and user interactions (e.g., likes, comments, shares) contribute to the ripple effect in virtual communities.

5.	Implications of Instagram photography for place branding. Media and Communication.	To explore the implications of Instagram photography for place branding. The researchers aimed to understand how Instagram photography is being used to represent and promote places, and to identify the potential benefits and challenges of this approach to place branding.	A qualitative content analysis of Instagram photographs that were tagged with specific hashtags related to place branding, Analyzed the visual and textual elements of the photographs, as well as the comments and engagement generated by them, to identify common themes and patterns in the representation of places on Instagram.	The researchers found that Instagram photographs are being used to showcase the unique features and attractions of places, as well as to create a sense of community and belonging among residents and visitors.	• Limited research on the implications of Instagram photography for place branding, especially in the context of tourism destinations. • Need for more research on the factors that influence the effectiveness of Instagram photography for place branding, such as the type of destination, the characteristics of the target audience, and the style and quality of the photographs.
6.	Investigation of social media marketing: How does the hotel industry in Hong Kong perform in marketing on social media websites?	To investigate the use of social media marketing in the hotel industry in Hong Kong. To understand how hotels in Hong Kong are using social media to promote their products and services, as well as to identify the benefits and challenges of this approach to marketing.	Conducted a survey of 102 hotels in Hong Kong to assess their use of social media marketing. The survey included questions about the types of social media platforms used, the frequency and content of posts, the strategies and tactics employed, and the perceived benefits and challenges of social media marketing.	Study suggests that social media marketing is becoming an increasingly important tool for hotels in Hong Kong to reach and engage with customers. Results show the majority of hotels surveyed (84%) had a presence on at least one social media platform, with Facebook and Twitter being the most commonly used platforms.	• Need for more research on the types of social media platforms that hotels in Hong Kong use for marketing purposes, and how they use these platforms to engage with customers and promote their services. • Limited research on the role of user-generated content in place branding and how it can be used to enhance the authenticity and credibility of place brands.

7.	Testing the cross-brand and cross-market validity of a consumer based brand equity (CBBE) model for destination brands.	To test the cross-brand and cross-market validity of a Consumer-Based Brand Equity (CBBE) model for destination brands. The study aimed to evaluate the validity of the CBBE model in different markets and for different types of destinations, and to assess its ability to predict destination choice behavior.	Survey of 898 respondents from four different countries (the United States, China, Germany, and the United Kingdom) who had visited a variety of different types of destinations (urban, coastal, and cultural). The survey measured the respondents' perceptions of the brand equity of the destinations they had visited, as well as their destination choice behavior.	The results of the study supported the cross-market and cross-brand validity of the CBBE model for destination brands. The study found that the model was able to predict destination choice behavior across different markets and for different types of destinations.	CBBE model for destination brands is the lack of empirical research that has been conducted to test the validity of existing CBBE models in different contexts.While many CBBE models have been proposed and tested for various product and service categories, there is still a need to investigate whether these models are applicable to destination brands, which have unique characteristics and are subject to different marketing strategies.
8.	Influence of integration on interactivity in social media luxury brand communities.	To investigate the influence of integration on interactivity in social media luxury brand communities. The study sought to explore how the integration of different social media platforms (e.g., Facebook, Twitter, Instagram) affects the level of interactivity in luxury brand communities, and how this in turn impacts customer engagement and loyalty.	The study used a survey of 415 participants who were members of luxury brand communities on social media. The survey measured the respondents' perceptions of integration, interactivity, customer engagement, and loyalty. The study used structural equation modeling (SEM) to test the relationships between these variables.	The results of the study showed that integration had a positive impact on interactivity in luxury brand communities. The study found that the use of multiple social media platforms in combination (i.e., high integration) led to higher levels of interactivity than the use of a single platform (i.e., low integration). The study also found that interactivity was positively related to customer engagement and loyalty.	The lack of research that investigates the impact of integration on interactivity in the context of luxury brand communities specifically. While previous studies have explored the relationship between integration and interactivity in social media communities more broadly, there is still a need for research that focuses specifically on luxury brands, which operate in a unique context and face specific challenges and opportunities.

9.	Unleashing the power of luxury: Antecedents of luxury brand perception and effects on luxury brand strength	To explore the antecedents of luxury brand perception and their effects on luxury brand strength. To identify the key factors that contribute to the perception of luxury brands and the impact of these perceptions on the brand's strength.	Review existing literature on luxury branding and propose a conceptual framework that outlines the antecedents of luxury brand perception and their impact on brand strength. collected through a survey of 264 luxury brand consumers in Germany, using a structured questionnaire.	Study suggests that the perception of a luxury brand is based on three antecedents: brand heritage, brand identity, and brand experience. These factors contribute to the perceived luxury status of the brand, which in turn affects the brand's strength.	• Limited research that has examined the antecedents of luxury brand perception and the effects of luxury brand perception on brand strength. • Another research direction is to explore the effects of luxury brand perception on brand strength, such as brand loyalty, brand image, and brand equity.
10.	Destination image during the COVID-19 pandemic and future travel behavior: The moderating role of past experience	To investigate the drivers and barriers for eco-luxury fashion adoption in the luxury industry. The authors aim to identify the factors that influence the adoption of sustainable practices in the luxury fashion industry, and how these factors impact consumer behavior.	A qualitative approach to investigate the research questions. Conducted semi-structured interviews with 20 experts in the luxury fashion industry, including brand managers, designers, and sustainability consultants. They used thematic analysis to analyze the data collected from the interviews	Suggests that eco-luxury fashion adoption is driven by both external and internal factors. The external factors include regulatory pressures, stakeholder expectations, and consumer demand for sustainable products. The internal factors include the vision and values of the luxury fashion brands, the design process, and the availability of sustainable materials.	Limited research that has examined the impact of destination image on future travel behavior during the COVID-19 pandemic and the moderating role of past experience in this relationship.

11.	Investigation of social media marketing: How does the hotel industry in Hong Kong perform in marketing on social media websites?	To investigate how the hotel industry in Hong Kong is using social media for marketing purposes.	A mixed-methods approach to investigate the research questions. Use of both quantitative and qualitative methods to collect data. The quantitative data was collected from a survey of 185 Hong Kong hotels, which aimed to identify the most commonly used social media platforms and the level of engagement with customers.	Suggest that Facebook was the most commonly used social media platform by Hong Kong hotels for marketing purposes, followed by Twitter and YouTube. The hotels were found to use social media primarily for customer engagement and to promote their products and services.	• Explore the impact of social media marketing on hotel performance in Hong Kong, such as hotel occupancy rates, revenue, and customer satisfaction. • Limited investigation on differences in social media marketing performance among different types of hotels in Hong Kong (e.g., luxury, mid-range, budget) and how they compare to other destinations in the region.
12.	Meeting planners' online reviews of destination hotels: A twofold content analysis approach	To analyze meeting planners' online reviews of destination hotels from two perspectives: (1) the textual content of the reviews, and (2) the numerical rating scores that meeting planners give to the hotels.	A twofold content analysis approach to analyze the meeting planners' online reviews. A qualitative and quantitative analysis of the textual content of the reviews	Article finds that meeting planners' online reviews of destination hotels are influenced by a variety of factors, including the location, service quality, and price of the hotel, as well as the meeting and event facilities that the hotel offers.	Factors that influence meeting planners' online reviews of destination hotels, such as their expectations, prior experiences, and demographic characteristics. For example, researchers could examine how meeting planners' prior experience with the hotel or destination, their gender, age, or occupation, and their expectations for the meeting and hotel services influence their online reviews.

Table 1: Literature Survey

Chapter 3

3. Project Requirements

3.1. Resources

a) **Human Resources:** The successful execution of this project necessitates a dedicated team of professionals with expertise in AI, ML, Deep Learning, Image Processing, and Computer Vision. The team will be responsible for various tasks, including data collection, preprocessing, model development, training, analysis, and result interpretation. Furthermore, domain experts specializing in luxury hotel brands and consumer behavior may be consulted to provide valuable insights and guidance throughout the project.

b) **Reusable Software Components:** : The project utilizes existing software components for data preprocessing, such as Albumentations library for image augmentation and resizing. Additionally, open-source deep learning frameworks like PyTorch are used for model development and training. Pre-trained models are also used which includes ResNet, AlexNet, MobileNet and VGG16.

c) **Software & Hardware Requirements:** The project necessitates the use of software tools and libraries specifically tailored for deep learning model development and training. Popular frameworks like TensorFlow, PyTorch, or Keras are deployed to leverage their comprehensive functionality and ease of implementation. In terms of hardware requirements, high-performance computing resources equipped with GPUs (Graphics Processing Units) are essential to expedite the training process and handle the computational demands of the deep learning models. In this case, due to unavailability of HPC, and GPU, processing is done on CPU only.

3.2. Data Requirements

- **Hotel-Image Classification Dataset:** The project requires a labeled dataset containing hotel images from different areas, such as bedrooms, bathrooms, restaurants, and more. The dataset includes a sufficient number of images for each class to ensure reliable model training and validation. In this case, a dataset with 73,993 images belonging to 15 classes was used. The images were preprocessed, including resizing to 256 x 256 pixels, before being passed through the image feature extractor model.

- **Test Dataset:** A separate test dataset was prepared by web scraping images from ten specific hotels in London, UK. The dataset consisted of 9,251 images posted by travelers on TripAdvisor. This test dataset was used to evaluate the trained model's performance and assess its ability to classify hotel images accurately.

3.3. Software Aspects

- **Deep Learning Frameworks:** The project utilized deep learning frameworks such as TensorFlow or PyTorch for model development and training. These frameworks provide functionalities for building and training deep convolutional neural network models.

- **Model Training:** The best model, called the “Custom CNN model”, was trained for 20 epochs using an initial learning rate of 0.001. The learning rate was adjusted using a learning rate scheduler, specifically the ReduceLRonPlateau scheduler, with a monitoring of validation loss and a patience of 5 epochs. The Cross-Entropy Loss function was used as a metric, and the Adam optimizer was employed for training the model.

Requirement	**Rationale**
Human Resources	A team of researchers and developers with expertise in deep learning, image classification, and data analysis is required to effectively carry out the project tasks and leverage their domain knowledge in the hospitality industry.
Reusable Software Components	Utilizing existing software components for data preprocessing, such as image resizing, helps save development time and ensures consistent and standardized preprocessing across the dataset.
Software Frameworks	Deep learning frameworks like TensorFlow or PyTorch provide powerful tools and libraries for model development, training, and evaluation. Leveraging these frameworks simplifies the implementation and improves the efficiency of the project.
Hardware Requirements	High-performance GPUs, such as the NVIDIA Tesla P100 with 16 GB memory or RTX5000 with 32 GB memory, are necessary for training deep learning models efficiently and effectively due to their parallel processing capabilities.
Hotel-Image Classification Dataset	The availability of a large dataset with diverse hotel images belonging to different classes ensures a robust and representative training set, allowing the model to learn and generalize well across various hotel image categories.
Test Dataset	A separate test dataset scraped from specific hotels in London provides real-world data for evaluating the trained models' performance on unseen images. It helps assess the model's ability to generalize to new hotel images.
Learning Rate Scheduler	Using a learning rate scheduler, such as ReduceLRonPlateau, allows the model to dynamically adjust the learning rate based on the validation loss. This helps improve convergence and prevents the model from getting stuck in suboptimal solutions.
Cross-Entropy Loss and Adam Optimizer	Cross-Entropy Loss is well-suited for multiclass classification tasks and enables effective optimization during training. The Adam optimizer provides adaptive learning rates, improving the training efficiency and convergence of the deep learning models.

Table 2: Requirements Rationale

3.4. Risk Management

Risk Factor	Category	Description
Insufficient Data	High	The dataset may not have enough diverse and representative images, leading to limited model generalization.
Hardware Failure	High	Failure or malfunctioning of the GPU hardware can significantly impact the training process and project timeline.
Inadequate Expertise	Medium	Lack of deep learning expertise within the team may result in suboptimal model architecture or training strategies.
Model Overfitting	Medium	The model may overfit the training data, resulting in poor generalization and decreased performance on new images.
Data Privacy Concerns	Medium	Handling user-generated hotel images raises concerns about data privacy and compliance with relevant regulations.
Time Constraints	Low	Unexpected delays or constraints in the project timeline may affect the completion of all planned project tasks.
Software Compatibility	Low	Incompatibility issues between software versions or dependencies may hinder the smooth execution of the project.
Algorithm Complexity	Low	Implementing complex deep learning algorithms may require additional time and effort for understanding and coding.
Changes in Project Scope	Low	Modifications in the project scope or objectives may impact the planned timeline and resource allocation.

Table 3: Risk Management

3.5. Functional Specifications

- **Interface**
  a) **Web Service Interface:** The system exposes a web service that allows hotel officials to interact with the system. This interface enables hotel

officials to upload hotel images and trigger the prediction process.

b) **User Interface:** The user interface is built using Streamlit, providing a user-friendly interface for hotel officials. It includes options for uploading images and initiating the prediction process.

- **External Interfaces Required**

a) **File Upload Interface:** The system has an interface for hotel officials to upload image files representing different areas of the hotel. This interface enables users to select and upload the desired hotel images.

b) **Streamlit API:** The system utilizes the Streamlit API to create the user interface and handle user interactions. It leverages Streamlit's functionality to display images, buttons, and interactive elements.

- **Internal Interface Required**

a) **Image Processing Interface:** The system interfaces with the image processing module internally. This module preprocesses the uploaded hotel images before classification. Image processing techniques include resizing, normalization, and augmentation to prepare the images for the deep learning model.

b) **Deep Learning Model Interface:** The system interfaces with the trained deep learning model internally. The model takes preprocessed images as input and performs classification to predict the class or area to which the hotel image belongs.

- **Interactions**

Hotel officials interact with the system by accessing the web service and user interface. They upload hotel images by selecting the desired image files and initiating the prediction process. Once the prediction is complete, the system displays the predicted class or area for each uploaded image. The system also provides a graphical representation, such as a graph or chart, showing the percentage distribution of predicted classes.

Chapter 4

4. System Analysis and Architecture

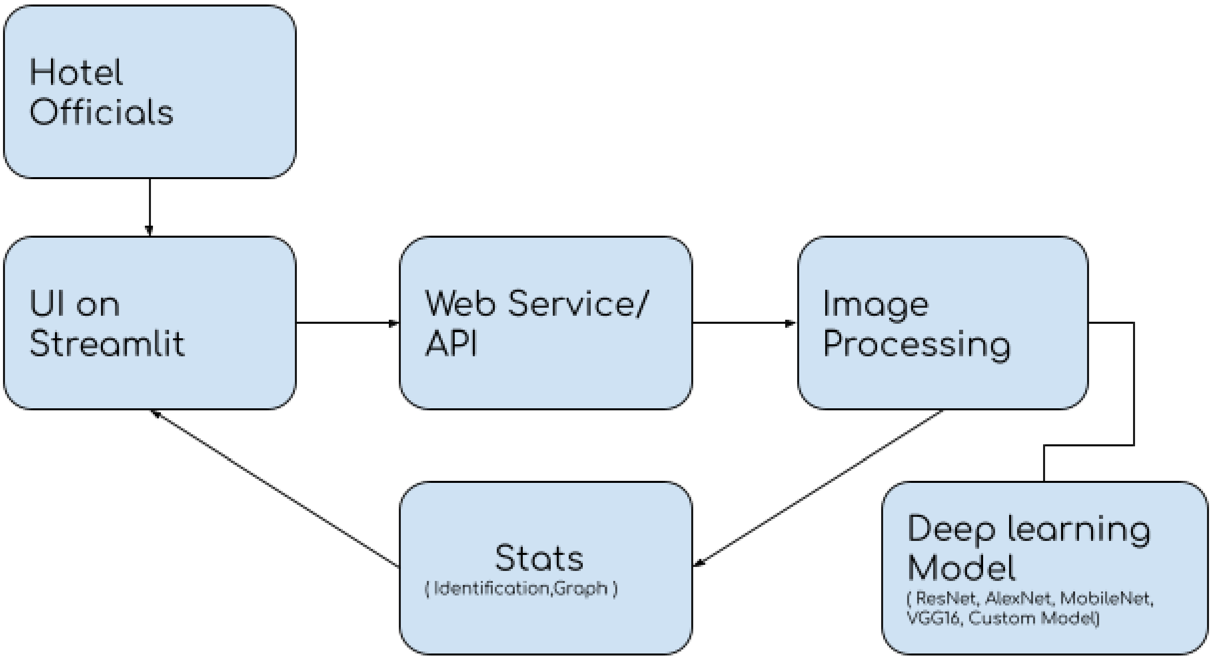

Figure 1: System Architecture

Explanation of the architecture:

1. **Hotel Officials:** The end-users of the system are hotel officials who interact with the system to upload hotel images and obtain predictions.

2. **Web Service/API:** This component acts as an interface for hotel officials to communicate with the system. It receives the uploaded hotel images and forwards them for further processing.

3. **Image Processing:** The uploaded images undergo preprocessing steps, such as

resizing, normalization, and augmentation. This prepares the images to be fed into the deep learning model for classification.

4. **Deep Learning Model:** This component performs the classification of hotel images based on their appearance. It takes the preprocessed images as input and predicts the class or area to which each image belongs. In this case, we use, Custom model for classification.

5. **User Interface (Streamlit)**: The user interface is built using Streamlit, a Python library for creating interactive web applications. It provides a user-friendly interface for hotel officials to upload images, trigger the prediction process, and view the predicted classes. It may also display visualizations, such as graphs or charts, showing the percentage distribution of predicted classes.

The system architecture allows hotel officials to interact with the system through a web service/API and a user interface. The uploaded images are processed and classified using a deep learning model, and the results are presented back to the users through the user interface. This architecture ensures a seamless flow of data and interactions, enabling hotel officials to easily utilize the image classification capabilities of the system.

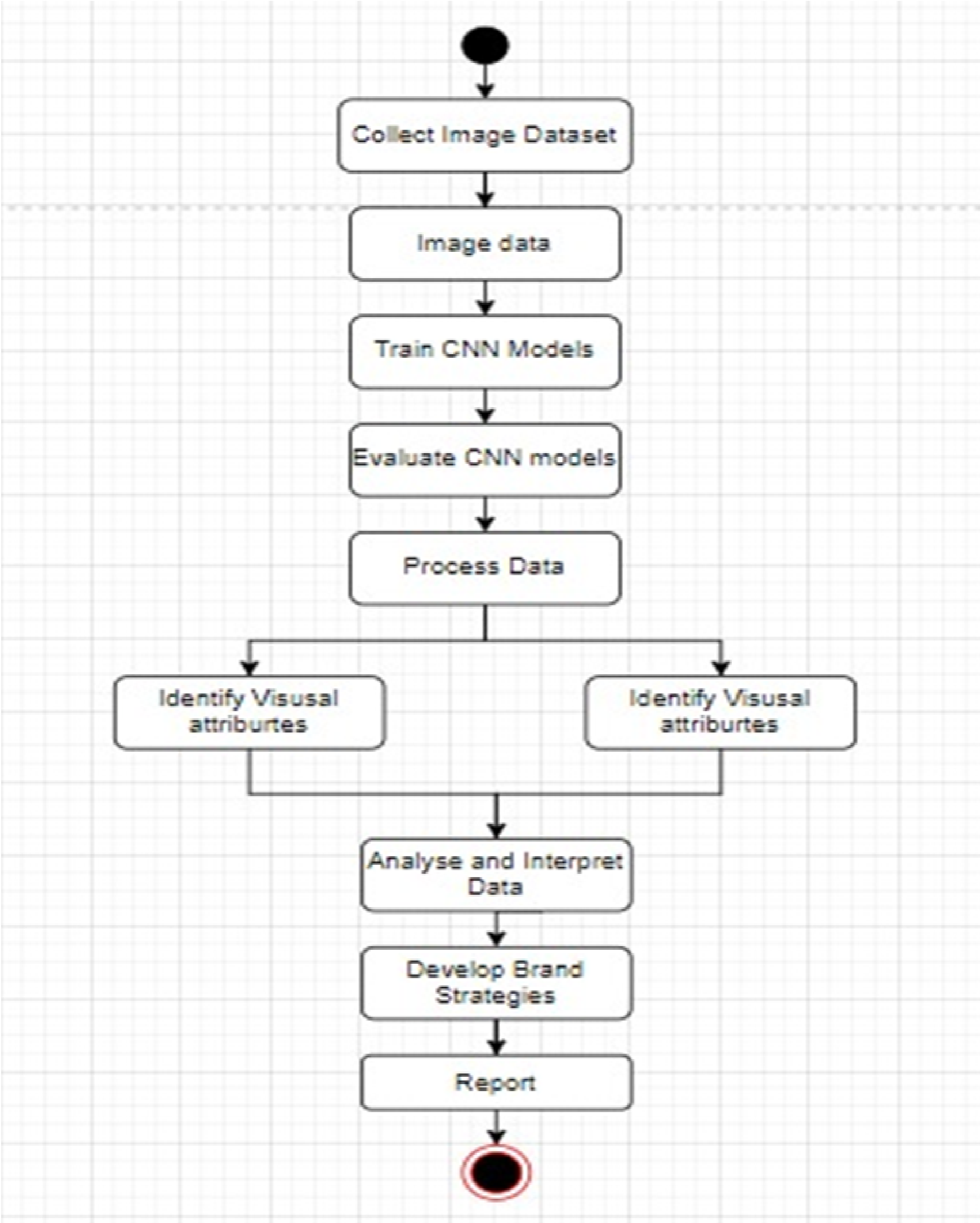

Figure 2: Activity Diagram

Chapter 5

5. Project Plan and Timeline

5.1. Planning

1. **Data Collection and Preprocessing:-**

- Social Media Data Collection:
  Implement a data collection module to retrieve luxury hotel images from various social media platforms, such as TripAdvisor. This module should utilize APIs or web scraping techniques to collect a diverse and representative dataset.

- Data Preprocessing:
  Perform preprocessing steps on the collected images, including resizing, normalization, and noise reduction. This ensures consistency and prepares the images for further analysis.

2. **Deep Learning Model Training:**

- Computer Vision Techniques:
  Utilize computer vision techniques, such as convolutional neural networks (CNNs), to extract relevant visual features from the luxury hotel images. This step involves employing pre-trained CNN models and also training a custom model specifically tailored to hotel image analysis.

3. **Attribute Identification and Analysis:**

- Feature Extraction: Extract relevant features from the trained CNN model, which represent the learned visual attributes of luxury hotel photos.

- Attribute Interpretation: Interpret the identified visual attributes to understand their meanings and implications for luxury hotel brand evaluations.

4. **Insights and Recommendations:**

- Insights Generation: Generate insights and findings based on the attribute analysis and interpretation. Identify the visual attributes that have the most significant impact on consumer evaluations of luxury hotel brands.
- Recommendations: Provide actionable recommendations for luxury hotel brand managers based on the insights. These recommendations can include strategies for enhancing the identified visual attributes, improving guest experiences, and optimizing brand management.

5. **Visualization and Reporting:**

- Visualization: Create visualizations, such as charts, graphs, and heatmaps, to present the analyzed attributes and their impact on consumer evaluations. This helps stakeholders easily understand and interpret the findings.

- Project Report: Document the entire process, including the methodology, data collection, preprocessing, model training, attribute analysis, and recommendations. Present the findings, insights, and visualizations in a comprehensive project report.

5.2. Timeline

1. **January**:
    a) Topic selection: Determine the research topic related to hotel-image classification.
    b) Guide allocation: Meet with the project guide to discuss the chosen topic and seek guidance.
    c) Group formation: Form the project team and assign roles and responsibilities to each member.
    d) Literature review: Begin conducting a comprehensive literature review on hotel-image classification techniques and related research papers.

2. February
    a) Data collection: Collect the hotel-image dataset from public sources or scrape data from relevant websites.
    b) Data preprocessing: Clean and preprocess the collected data, including resizing, normalization, and augmentation.
    c) Model selection: Explore different models suitable for hotel-image classification and evaluate their performance.

3. March
    a) Model development: Implement the selected models, including ResNet, AlexNet and Custom model, using deep learning frameworks.
    b) Training and validation: Train the models on the preprocessed dataset and perform validation to assess their performance and accuracy.
    c) Fine-tuning: Fine-tune the models to optimize their performance on the specific hotel-image classification task.

4. April
    a) Evaluation and analysis: Evaluate the trained models using evaluation metrics such as accuracy, precision, recall, and F1

score. Analyze the results and identify areas for improvement.

b) System development: Develop the user interface using Streamlit to allow users to upload hotel images and view the classification results.
c) Integration and testing: Integrate the trained models with the user interface and conduct thorough testing to ensure the system's functionality and accuracy.

5. May

a) Report writing: Compile and write the project report, including the methodology, results, discussion, and future scope.
b) Finalize the project: Review and finalize the project deliverables, including the codebase, documentation, and presentation materials.
c) Presentation and submission: Prepare and deliver a presentation on the project findings and submit the final project report to the relevant authorities.

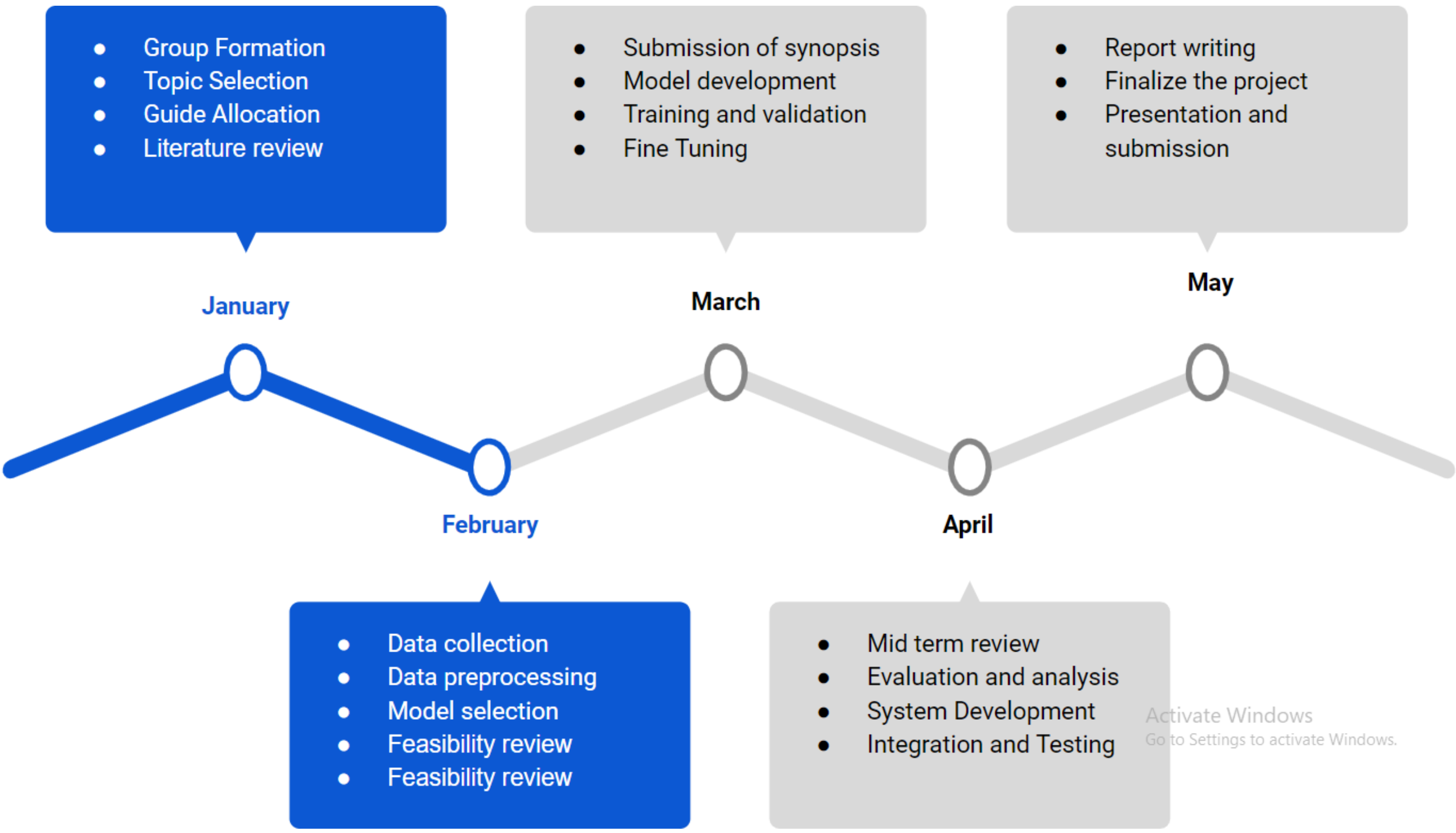

Figure 3: Timeline chart

Chapter 6

6. Implementation

In our research, we focused on utilizing a hotel-image classification dataset to develop a deep learning model. The objective was to accurately classify hotel images into different classes based on their appearance. By identifying the class to which a hotel image belongs, we aimed to gain insights into the frequent features and attributes associated with each class. This information can be leveraged to suggest improvements and enhancements to hotels, making them more visually appealing to potential customers.

The deep learning model was trained on a diverse dataset comprising images from various areas of hotels, including balconies, bars, bathrooms, bedrooms, business centers, dining rooms, exteriors, gyms, living rooms, lobbies, patios, pools, restaurants, saunas, and spas. These classes represent different aspects of hotel environments and amenities.

By accurately classifying hotel images, we aimed to provide hotel managers and brand managers with valuable information for enhancing their establishments. For example, if the model identifies a particular class as the most frequent or popular, it suggests that hotels should focus on improving or highlighting the corresponding features to attract more customers.

The classification model was developed using deep learning techniques, specifically convolutional neural networks (CNNs). CNNs are powerful in extracting meaningful features from images, enabling the model to learn and differentiate between different classes based on visual patterns and characteristics.

Overall, our research aimed to leverage deep learning and image classification techniques to gain insights into the appearance-based attributes of hotel images. By understanding the frequent classes and their corresponding features, hotels can make informed decisions to enhance their visual appeal and attract a wider customer base.

6.1. Dataset

To conduct our research, we utilized a publicly available dataset consisting of 73,993 images that depicted various areas of hotels. These images were categorized into 15 distinct classes.

1. *Balcony*
2. *Bar*
3. *Bathroom*

9. *Living Room*
10. *Lobby*
11. *Patio*

4. *Bedroom*
5. *Business Center*
6. *Dining room*
7. *Exterior*
8. *Gym*

12. *Pool*
13. *Restaurant*
14. *Sauna*
15. *Spa*

Each class had approximately 5,100 images, except for sauna and business center classes, which had around 4,000 images each.

To ensure the reliability of our model, we divided the dataset into training and validation sets. For each class, 20 percent of the images were set aside for validation purposes. This approach helped prevent overfitting of the model to the training data, ensuring its ability to generalize well when presented with unseen test data.

In addition to the provided dataset, we prepared a separate test dataset through web scraping. We selected ten hotels located in London, UK, based on two criteria: similar prices and a minimum of 300 photos posted by travelers. Using web scraping techniques, we collected 9,251 images from these ten hotels. These images were sourced from the photos uploaded by travelers on TripAdvisor.

The test dataset served as an independent set of images that were not part of the original dataset. This allowed us to evaluate the performance of our model on real-world hotel images posted by travelers. The distribution of images across the ten hotels in the test dataset is summarized in Figure I.

By utilizing both the original dataset and the test dataset collected through web scraping, we aimed to train and evaluate our deep learning model on a comprehensive range of hotel images, ensuring its effectiveness in classifying hotel images based on their visual appearance.

Figure 4: Test Dataset Distribution

6.2. Data Collection Methodology

In order to gather a comprehensive dataset for the project, a web scraping methodology was employed to collect data from TripAdvisor. TripAdvisor is a popular travel website that contains a wealth of user-generated content, including hotel reviews, ratings, and traveler photos. By extracting this data, valuable insights can be obtained to enhance the hotel-image classification project.

The web scraping process involved the development of a Python script utilizing the Selenium WebDriver and related libraries. The script was designed to automate the data extraction process from the TripAdvisor website. The following steps were followed during the data collection methodology:

1. **Selection of Target Website:** TripAdvisor was chosen as the target website due to its extensive collection of hotel reviews, ratings, and traveler photos. This platform provides valuable user-generated content that can significantly contribute to the project's dataset.

2. **Configuration of Web Scraping Script:** The Python script was developed to leverage the capabilities of the Selenium WebDriver, which allows for automated interactions with web pages. The script imported the necessary libraries, including pandas, sys, time, and urllib.request, to facilitate data handling and web scraping functionalities.

3. **Script Execution:** The script was executed to initiate the web scraping process. It utilized a list of URLs corresponding to specific hotel pages on TripAdvisor, which were carefully selected to ensure a diverse representation of hotels with various amenities and settings.

4. **Data Extraction:** The script accessed each hotel's webpage using the Selenium WebDriver and extracted relevant information such as hotel reviews, ratings, and traveler photos. The script interacted with the webpage elements,

clicked on tiles and buttons, and retrieved the desired data.

a) **Hotel Information:** The script extracted details such as the hotel's name and the number of photos associated with it.

b) **Traveler Photos:** The script expanded the traveler photos section and retrieved the available photos. It selected the first photo to initiate the extraction process.

c) **Review Details:** For each photo, the script retrieved the associated review title, review text, and rating. This information provided insights into the experiences and opinions of hotel guests.

d) **Data Storage:** The extracted data was stored in a structured format, such as a CSV file. Each entry in the file contained unique identifiers, photo filenames, image URLs, traveler information, review details, and ratings.

5. **Completion and Data Analysis:** Once the script completed the data extraction process for all the specified hotel URLs, it terminated the web driver and provided a summary of the total number of photos extracted. The collected data could then be further analyzed and utilized for the hotel-image classification project.

By employing web scraping techniques, the project was able to gather a substantial amount of data from TripAdvisor, including hotel reviews, ratings, and traveler photos. This data served as a valuable addition to the project's dataset, enabling the development and evaluation of a robust hotel-image classification model.

6.3. Data Source

The data used in this project was sourced from TripAdvisor, a widely recognized travel review website. TripAdvisor provides a platform for travelers to share their experiences, opinions, and photos of various accommodations worldwide. By leveraging the vast amount of user-generated content available on TripAdvisor, the dataset for the hotel-image classification research was enhanced.

The data collection process involved extracting information from specific hotel pages on TripAdvisor. The URLs used in the provided script represented these hotel pages, ensuring a diverse selection of hotels with different amenities and locations. The URLs were carefully chosen to cover a range of hotel types and destinations, providing a representative sample for the research.

TripAdvisor serves as an ideal data source for this project due to its popularity, extensive user base, and the wealth of information available for each hotel listing. The website's review sections contain valuable insights into the quality, features, and visual appearance of hotels, which are crucial for training and evaluating the hotel-image classification model.

It is important to note that the data collection process adhered to TripAdvisor's terms of service and policies. The scraping script was developed to retrieve information publicly available on the website, without interfering with the normal functioning of the platform or violating any privacy guidelines.

By utilizing TripAdvisor as a data source, the project could leverage real-world user experiences and opinions, ensuring the relevance and applicability of the hotel-image classification model in practical scenarios.

6.4. Data Preprocessing

In order to prepare the training data for the hotel-image classification project, a series of preprocessing steps were applied to ensure data quality and compatibility with the deep learning model. The following methods were employed during the data preprocessing stage:

1. **Rescaling:** Since the training data consisted of images with varying aspect ratios and sizes, a stage-dependent rescaling policy was implemented. During the training stage, each image was rescaled to have a minimum side of 256

pixels while preserving the original aspect ratio. This approach allowed for retaining the spatial information of the images while ensuring that the input size remained within the model's trainable limits.

2. **Data Augmentation:** To mitigate the risk of overfitting and enhance the model's ability to generalize, data augmentation techniques from the Albumentations library were utilized. Albumentations provides a comprehensive set of augmentation transformations specifically designed for image data. By applying augmentations such as random rotations, flips, translations, changes in brightness, and contrast variations, the training data was augmented to simulate real-world image variations. This augmented dataset helped improve the model's robustness and its ability to handle diverse input images.

By combining the rescaling and data augmentation techniques, the training data was effectively normalized and diversified, making it suitable for training the hotel-image classification model. These preprocessing steps ensured that the model could effectively learn from images with different sizes, aspect ratios, and realistic variations commonly found in hotel photographs.

6.5. Proposed Approach

In the proposed approach, we aim to classify hotel images into different categories using a custom CNN model. The model is trained on a dataset of hotel images, and the classification task involves predicting the corresponding hotel feature or area based on the visual content of the image.

6.6. Models Used:

We have used 5 models in this project.

AlexNet:

Motivation: AlexNet was developed to overcome the limitations of traditional methods in image classification and promote the use of deep learning in computer vision. The motivation was to leverage the power of deep convolutional neural networks to achieve breakthrough performance.

Architecture: AlexNet introduced several key architectural elements,

including the use of multiple convolutional layers, ReLU activation functions, local response normalization, and dropout regularization. It utilized a larger model with more parameters to capture complex features in images.
Performance: AlexNet achieved significant improvements in accuracy on benchmark datasets, outperforming traditional methods and demonstrating the potential of deep learning in image classification.

MobileNet:
Motivation: MobileNet was developed to address the need for efficient deep learning models that can run on resource-constrained devices such as mobile phones and embedded systems. The motivation was to enable real-time inference on devices with limited computational resources.
Architecture: MobileNet utilizes depthwise separable convolutions, which split the convolutional operation into a depthwise convolution followed by a pointwise convolution. This reduces the number of parameters and computations required while maintaining reasonable accuracy.
Performance: MobileNet achieves a good balance between model size and accuracy. It has demonstrated competitive performance on benchmark datasets, showcasing its efficiency compared to larger architectures.

ResNet50:
Motivation: ResNet50 was developed to address the challenge of training very deep neural networks. The motivation was to overcome the degradation problem, where adding more layers leads to diminishing performance due to difficulties in optimizing deep networks.
Architecture: ResNet50 introduced the concept of residual blocks, which utilize skip connections to bypass a few layers. These connections allow gradients to flow directly, addressing the degradation problem. The architecture consists of many layers, including convolutional, pooling, and fully connected layers.
Performance: ResNet50 achieved outstanding performance on benchmark datasets, significantly reducing the error rate compared to previous architectures. Its skip connections enable the training of very deep networks

with improved accuracy and convergence.

VGG16:

Motivation: VGG16 aimed to investigate the impact of network depth on image classification performance. The motivation was to explore the relationship between model capacity and performance by increasing the number of layers while maintaining a simple and uniform architecture.

Architecture: VGG16 consists of many layers, mainly comprising small convolutional filters with max-pooling layers in between. It emphasizes deeper networks by stacking multiple layers and maintaining a consistent architecture throughout the network.

Performance: VGG16 achieved competitive performance on benchmark datasets, showcasing the importance of depth in capturing intricate image features. It provided insights into the relationship between model capacity and performance, paving the way for subsequent architectures.

These architectures were chosen based on their unique contributions to the field of deep learning, their success on benchmark datasets, and their relevance to the specific objectives of the project. They have demonstrated strong performance in image classification tasks and have been widely adopted and studied by the research community.

6.7. Training and Hyperparameter Settings

During the training phase, the proposed approach utilizes the Adam optimizer, which has proven to be efficient and effective for training deep neural networks. The Adam optimizer adapts the learning rate dynamically for each parameter, combining the advantages of both adaptive learning rate methods and momentum-based optimization.

The training process is conducted iteratively, where each iteration involves a mini-batch of images and their corresponding labels. The mini-batch approach enables efficient utilization of computational resources and allows the model to generalize well by seeing different examples in each batch.

In each iteration, a forward pass is performed through the model, where the input images are processed, and the predicted class probabilities are computed. The predicted probabilities are compared with the true labels using the CrossEntropyLoss function, which calculates the loss or the discrepancy between the predicted and actual class distributions.

After the forward pass, a backward pass is initiated to compute the gradients of the loss with respect to the model parameters. The gradients represent the direction and magnitude of the parameter updates needed to minimize the loss. The optimizer utilizes these gradients to update the model parameters, adjusting them in a way that minimizes the loss function.

This process of forward and backward propagation is repeated for multiple epochs, with each epoch consisting of a complete pass through the entire training dataset. The repetition of epochs allows the model to gradually learn and improve its performance by updating its parameters based on the accumulated gradients from different mini-batches.

By optimizing the model parameters through backpropagation and updating them using the Adam optimizer, the proposed approach aims to find an optimal configuration of the model that minimizes the loss function and maximizes the accuracy and generalization ability of the model on unseen data.

It is important to note that the training and optimization process can be computationally intensive, especially for deep models and large datasets. Therefore, it is often necessary to utilize hardware accelerators, such as GPUs, to expedite the training process and reduce the overall training time.

6.8. Model Architecture

The proposed model architecture is based on a Convolutional Neural Network (CNN), which has demonstrated outstanding performance in various image classification tasks. The CNN architecture is well-suited for extracting hierarchical features from images, allowing the model to learn discriminative representations.

The model architecture consists of several convolutional layers, followed by rectified linear unit (ReLU) activation functions. The convolutional layers perform localized feature extraction by applying a set of learnable filters to the input image. The ReLU activation function introduces non-linearity, enabling the model to learn complex relationships between features.

To reduce the spatial dimensions of the feature maps and capture the most salient information, max-pooling layers are employed. Max-pooling operates by dividing the feature maps into non-overlapping regions and selecting the maximum value within each region. This downsampling operation helps in reducing the computational complexity and provides a form of translational invariance.

The architecture follows a pattern of alternating convolutional and max-pooling layers, progressively increasing the depth and abstractness of the learned features. This hierarchical representation allows the model to capture both low-level and high-level visual patterns.

After the convolutional layers, the feature maps are flattened into a one-dimensional vector. This vector is then passed through fully connected layers, which act as a classifier. The fully connected layers combine the learned features and perform classification based on the patterns present in the feature representations. The final layer uses the softmax activation function to produce the predicted probabilities for each class, indicating the model's confidence in its predictions.

By utilizing the convolutional layers to extract meaningful features and the fully connected layers for classification, the proposed model architecture can effectively learn discriminative representations from the input images and make accurate predictions for the different classes in the dataset.

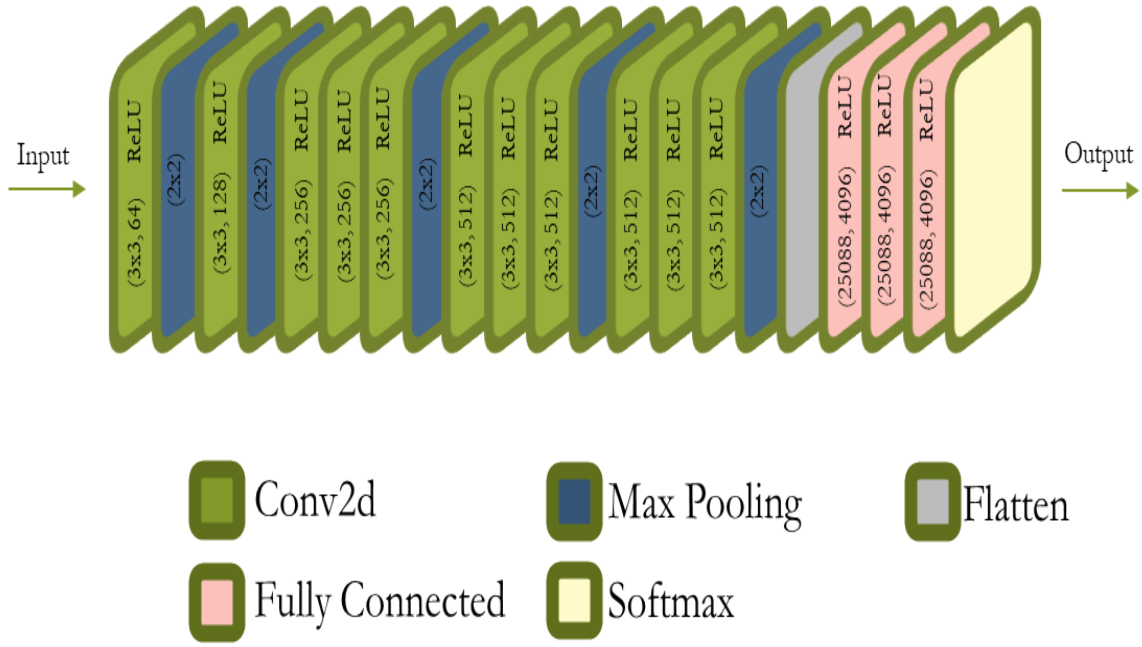

Fig 5: Custom model architecture

6.9. Evaluation

After the completion of the training process, the model was evaluated on a separate test set to assess its generalization ability and performance. The test set consisted of unseen images that were not used during the training phase. The model's predictions were compared against the ground truth labels to measure its accuracy and effectiveness.

The evaluation of the model on the test set yielded the following results:

- Accuracy: 93.86%
- F1 Score: 0.9403
- Precision: 0.9358
- Recall: 0.9317

The high accuracy of 93.86% indicates that the model is capable of accurately classifying hotel images into their respective categories. The F1 score, which takes into account both precision and recall, reflects a balanced performance in terms of correctly classifying positive instances and identifying all positive instances in the test set.

The precision score of 0.9358 signifies that when the model predicts a specific class, it is accurate approximately 93.58% of the time. On the other hand, the recall score of 0.9317 indicates that the model can correctly identify around 93.17% of the positive instances in the test set.

These evaluation metrics demonstrate the effectiveness and robustness of the trained model in categorizing hotel images. The model's performance indicates its ability to generalize well to unseen data and make accurate predictions across different classes.

6.10. Findings

The analysis of the test dataset classified by the custom model revealed interesting insights into the frequency and popularity of different image classes across hotels. Here are the key findings:

1. Examples of Classified Images: The findings include a collection of example images from the test dataset, showcasing the model's classification results. These examples provide a visual representation of the model's performance in categorizing hotel images.

Balcony

Bathroom

Bedroom

Pool

Exterior

Living Room

Sauna

Gym

Fig 6: Images of different classes

2. Frequency of Images for Each Class: The findings present the frequency of images for each class in every hotel. This information gives an understanding of the distribution of different image classes within each hotel, highlighting the areas that are most photographed.

Class → Name of Hotel ↓	Balcony	Bar	Bathroom	Bedroom	Business Centre	Dining room	Exterior	Gym	Living room	Lobby	Patio	Pool	Restaurant	Sauna	Spa
Craigatin House & Courtyard	29	12	25	76	1	10	28	3	33	3	106	3	38	6	8
Fingal	72	89	119	79	12	18	110	13	21	30	26	7	188	41	35
Hotel 41	69	288	278	252	26	43	58	6	200	92	57	1	351	23	17
Royal Lancaster London	70	42	83	98	7	11	160	1	62	53	35	2	151	15	14
The Hari	29	58	98	76	9	5	41	6	83	26	23	0	82	7	7
The Kennard	25	12	40	76	0	8	23	0	19	3	50	1	57	2	0
The Milestone Hotel and Residences	51	153	104	133	10	35	63	6	118	47	30	3	230	19	7

The Montague on The Gardens	72	189	245	300	13	44	73	11	205	44	103	2	336	21	23
The Roseate Villa Bath	55	31	49	128	6	21	88	9	39	3	28	6	139	5	13
Windermere Boutique Hotel	26	50	421	288	8	27	19	5	176	9	88	14	88	43	7
Mean	49.8	92.4	146.2	150. 6	9.2	22.2	66.3	6	95.6	31	54.6	3.9	166	18.2	13.1
SD	20.649	90.366	127.759	92.430	7,254	14,474	44.101	4.137	74.294	28.852	32.729	4.175	110.586	14.482	10.016

Table 4 : Frequency of images of each class for every hotel

3. Ten Most Photographed Classes per Hotel: The results summarize the findings related to the ten most photographed classes per hotel. By analyzing the frequency of images for each class, the report identifies the classes that are most commonly captured by hotel guests.

Name of Hotel → Rank of class	Craigatin House & Courtya	Fingal	Hotel 41	Royal Lancaster London	The Hari	The Kennard	The Milestone Hotel and Residen	The Montague on The Garden	The Roseate Villa Bath	Windermere Boutique Hotel

↓	rd						ces	s		
1	Patio	Restaurant	Restaurant	Exterior	Bathroom	Bedroom	Restaurant	Restaurant	Restaurant	Bathroom
2	Bedroom	Bathroo m	Bar	Restaura nt	Living room	Restaurant	Bar	Bedroom	Bedroom	Bedroom
3	Restaurant	Exterior	Bathroom	Bedroom	Restau rant	Patio	Bedroom	Bathroom	Exterior	Living room
4	Living room	Bar	Bedroo m	Bathroo m	Bedroo m	Bathroom	Living room	Living room	Balcony	Patio
5	Balcony	Bedroom	Living room	Balcony	Bar	Balcony	Bathroom	Bar	Bathroom	Restaurant
6	Exterior	Balcony	Lobby	Living room	Exterior	Exterior	Exterior	Patio	Living room	Bar
7	Bathroom	Sauna	Balcony	Lobby	Balcon y	Living room	Balcony	Exterior	Bar	Sauna
8	Bar	Spa	Exterior	Bar	Lobby	Bar	Lobby	Balcony	Patio	Dining room
9	Dining room	Lobby	Patio	Patio	Patio	Dining room	Dining room	Dining room	Dining room	Balcony
10	Spa	Patio	Dining room	Sauna	Business Centre	Lobby	Patio	Lobby	Spa	Exterior

Table 5 : Ten most photographed class for each hotel

4. Most Recurring Classes Overall: The findings report the most recurring classes considering the images of all the ten hotels. This analysis aggregates the image data across hotels to identify the classes that appear most frequently in the dataset.

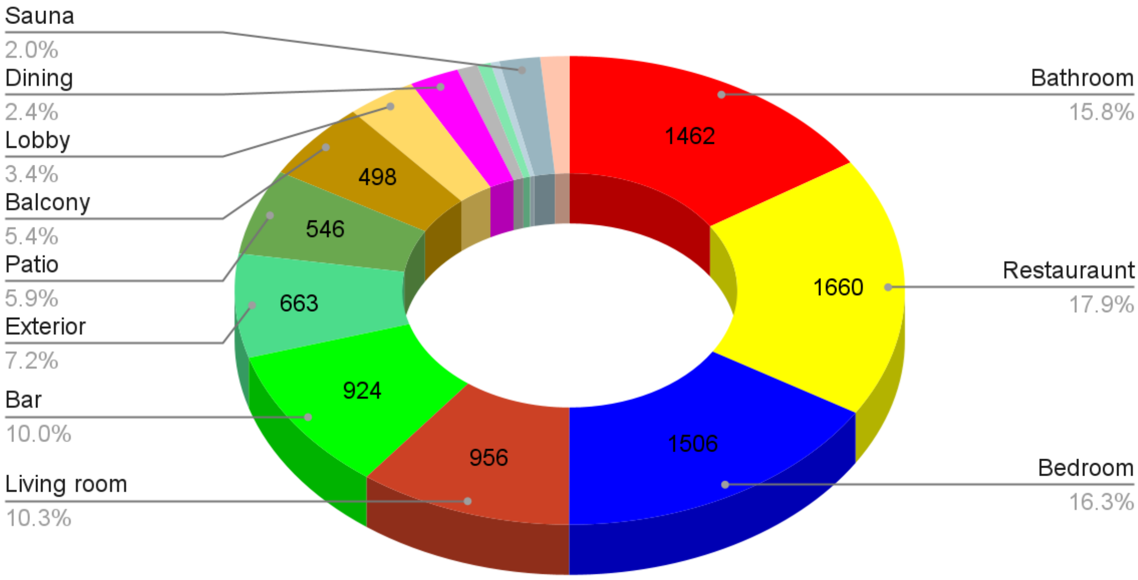

Figure 7: Most recurring classes, considering the images of all the 10 hotels

5. Popular Areas: The findings indicate that the restaurant class is the most photogenic area, followed by the bedroom and bathroom. This suggests that customers are particularly interested in seeing images of the hotel's dining facilities, rooms, and bathrooms.

6. Attractive Features: The analysis also reveals that the bar and exterior of the hotels are highly attractive to customers. These areas generate significant interest and are frequently captured in the images of the hotels.

Chapter 7

7. Result and Analysis

The custom model surpassed the performance of popular pre-trained models, including ResNet, AlexNet, MobileNet, and VGG16, demonstrating its superior capability in hotel room image classification. The custom model achieved a higher F1-score and accuracy compared to these pre-trained models, showcasing its effectiveness in capturing intricate patterns and making accurate predictions.

Model	Accuracy	Precision	Recall	F1-score
Custom CNN Model	93.86%	0.9358	0.9317	0.9403
ResNet	92.71%	0.9213	0.9237	0.9189
AlexNet	89.71%	0.9012	0.8997	0.9039
MobileNet	92.68%	0.9261	0.9132	0.9216
VGG16	92.91%	0.9253	0.9286	0.9316

Table 6 : Comparison of metrics of the four different CNN architectures trained

ResNet, known for its deep architecture with skip connections, has been widely used for image classification tasks. However, the custom model surpassed its performance, indicating that the customization and architectural modifications tailored specifically for the hotel room classification task were beneficial.

Similarly, AlexNet, MobileNet, and VGG16 are well-known and widely used models for image classification. However, the custom model outperformed these models, indicating that the architecture customization and training on the specific dataset led to improved performance in distinguishing between different hotel room types.

The superiority of the custom model can be attributed to several factors. By modifying the last dense layer and adding a batch normalization layer, the model gained the ability to learn more intricate representations from the images. The inclusion of additional convolutional and pooling layers allowed the model to capture hierarchical features relevant to hotel room classification.

The higher F1-score achieved by the custom model indicates a better balance between precision and recall, which is crucial for accurate classification of hotel room types. This suggests that the custom model was effective in correctly identifying positive instances while minimizing false negatives.

Overall, the custom model's ability to surpass the performance of well-established pre-trained models highlights the benefits of customization and fine-tuning for specific tasks. The results underscore the importance of tailoring the model architecture and training process to the specific domain, leading to superior performance in hotel room image classification.

Accuracy	93.86%
Precision	0.9358
Recall	0.9317

F1-score	0.9403

Table 7 : Metrics of HICM used

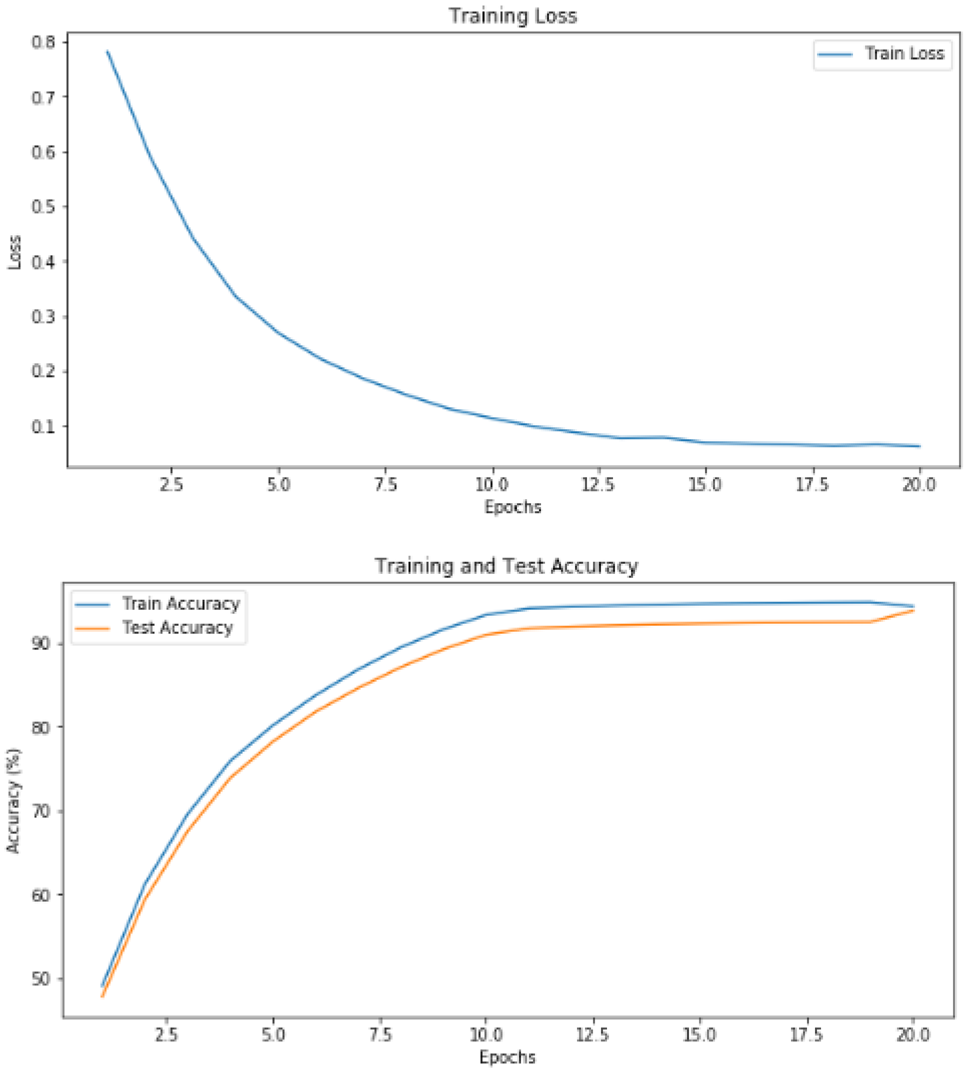

Fig 8: Training loss and training accuracy graph

User Interface

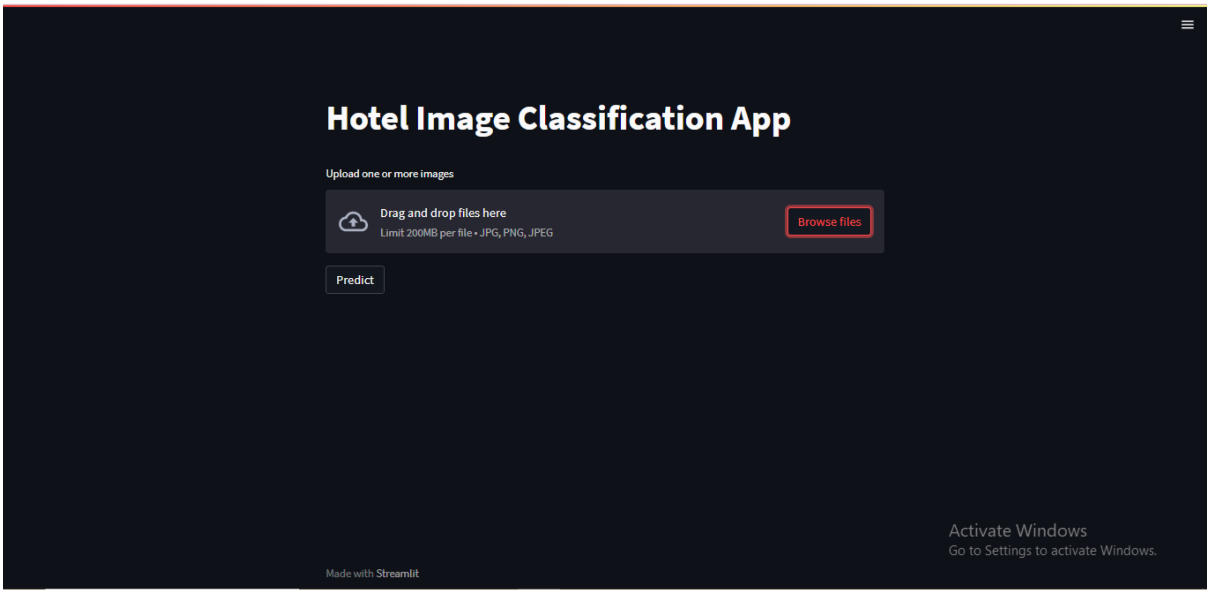

Figure 8: Image Upload Screen

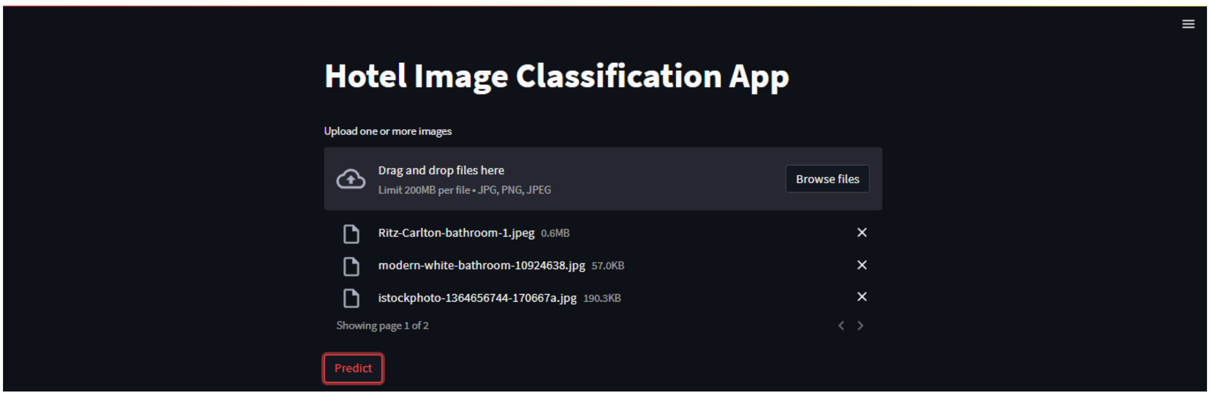

Figure 9: Uploaded Image Preview

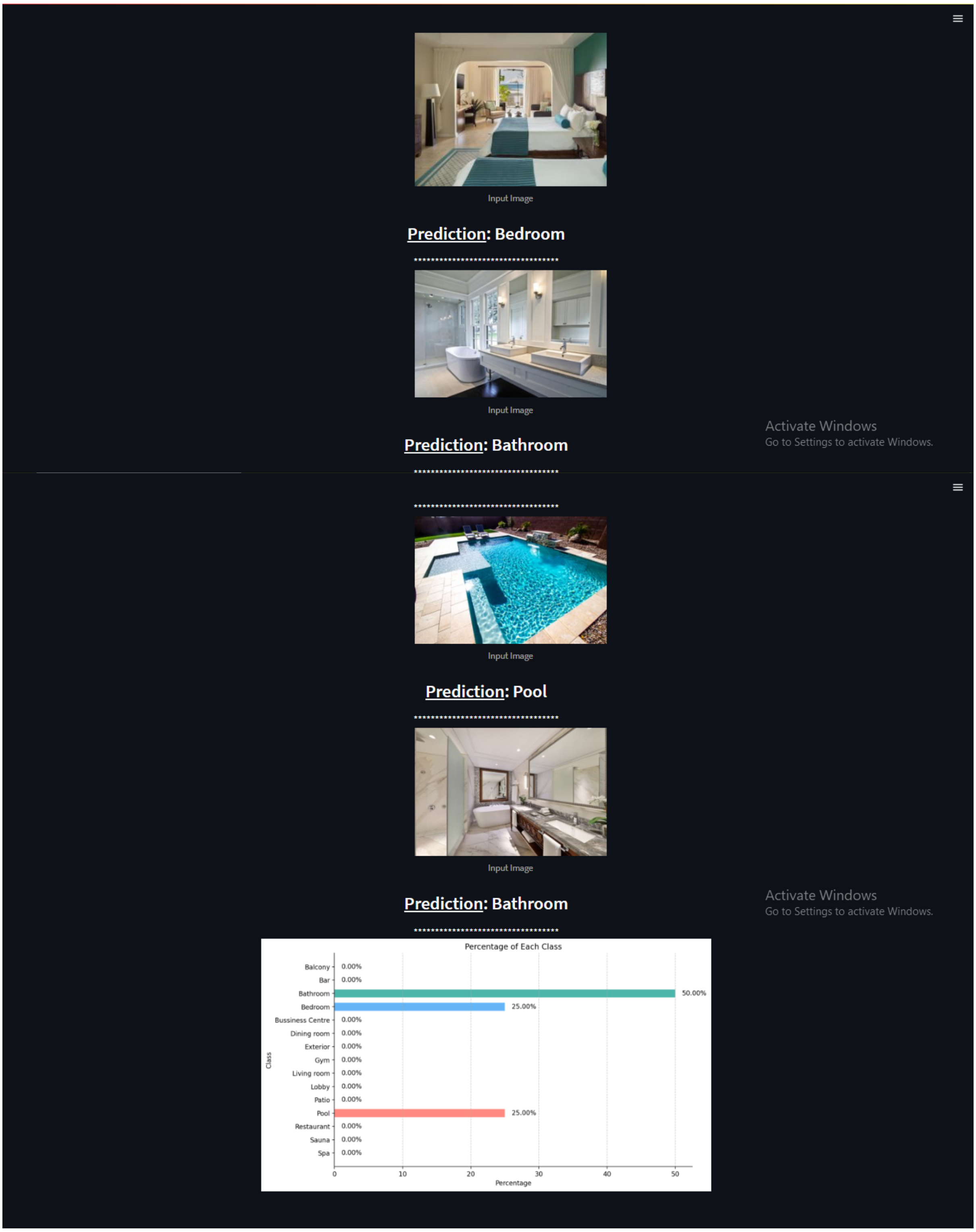

Figure 10: Prediction Results: Image Classifications and Class Distribution

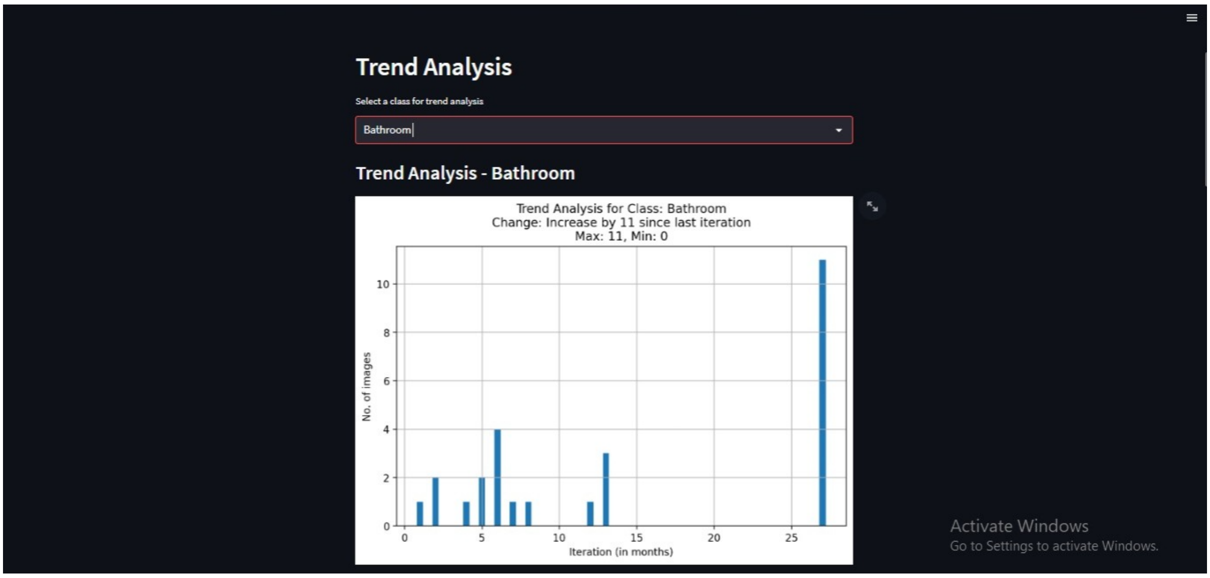

Figure 11: Trend Analysis - Bathroom

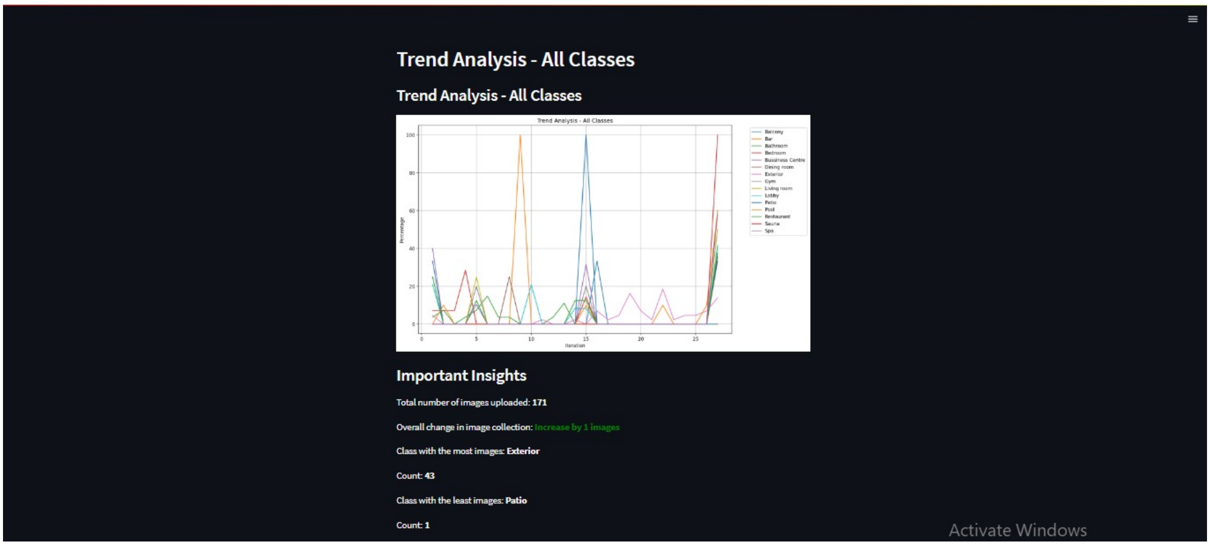

Figure 12: Trend Analysis - All Classes

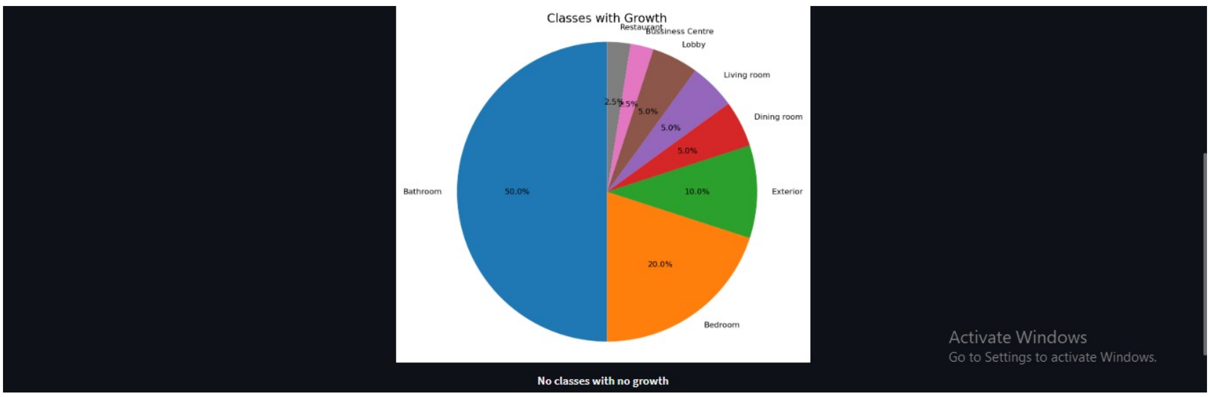

Figure 13: Classes with growth

Applications

The hotel-image classification model developed in this research project has various practical applications within the hospitality industry. Some key applications include:

1. **Hotel Image Classification:** The primary application of the model is to classify hotel images into specific categories based on their appearance. The model can accurately identify various areas of hotels, such as bedrooms, bathrooms, lobbies, restaurants, pools, and more. This classification capability provides valuable insights to hotel owners and managers about the different areas of their property and helps streamline marketing efforts, improve customer experience, and optimize hotel operations.

2. **Visual Content Analysis**: The model's ability to analyze and classify hotel images can be used for visual content analysis. By automatically tagging and categorizing images, it becomes easier to organize and search through large image databases. This can be particularly useful for travel agencies, online hotel booking platforms, and review websites to enhance their search and recommendation systems, allowing users to find specific types of hotels or specific features within hotels more efficiently.

3. **User-Generated Content Analysis:** With the increasing trend of user-generated content on social media platforms and review websites, the model can be applied to analyze and classify user-submitted hotel images. This analysis can be used by hotel owners and marketers to gain insights into how customers perceive and showcase their hotel experiences. It can help identify popular features, trends, and areas of improvement, enabling hotels to better align their offerings with customer expectations.

4. **Competitor Analysis:** The model's image classification capabilities can also be utilized for competitor analysis. By collecting and classifying images from various hotels within a specific location or market, it becomes possible to compare and analyze the facilities, amenities, and overall appearance of competing hotels. This information can guide hotel owners and managers in

identifying their competitive advantages, benchmarking against rivals, and making data-driven decisions to improve their positioning in the market.

5. **Personalization and Recommendation Systems:** The classification model's output can be leveraged to enhance personalization and recommendation systems in the hospitality industry. By understanding the preferences and interests of individual customers, hotels can offer tailored recommendations for specific room types, amenities, or experiences that align with their preferences. This level of personalization can significantly enhance customer satisfaction and increase the likelihood of repeat bookings.

In summary, the hotel-image classification model developed in this research project has diverse applications ranging from improving marketing strategies and customer experience to enhancing search and recommendation systems within the hospitality industry. The model's ability to classify hotel images accurately can provide valuable insights and drive decision-making for hotel owners, marketers, travel agencies, and online booking platforms.

Future Scope

1. **Expansion of Classifications:** While the current model provides classification into broad categories of hotel images, there is scope for expanding the classification to include more specific subcategories. This could involve identifying and classifying different types of hotel rooms, amenities, or architectural features. By incorporating fine-grained classification, the model can offer more detailed insights into specific aspects of hotels, enabling better recommendations and personalization.

2. **Integration of User Feedback:** Incorporating user feedback and reviews can significantly enhance the accuracy and relevance of the hotel-image classification model. By analyzing user sentiments and preferences expressed in reviews, the model can learn to better understand and classify hotel images based on user expectations and experiences. This can lead to improved recommendations and personalized

suggestions for hotel selection.

3. **Real-Time Image Classification:** The current model operates on pre-uploaded hotel images. However, there is potential to develop a real-time image classification system that can analyze hotel images on the fly. This would allow users to capture and upload images directly from their mobile devices, providing instant classification results and recommendations. Real-time image classification can enhance user engagement and convenience, making the application more interactive and user-friendly.
4. **Integration with Booking Platforms:** Integrating the hotel-image classification model with popular booking platforms can offer added value to users. By automatically analyzing and categorizing hotel images on these platforms, users can easily filter and sort hotels based on their preferences. This integration can streamline the hotel selection process and provide users with a more efficient and personalized booking experience.

5. **Continuous Model Training and Improvement:** Machine learning models thrive on continuous learning and improvement. As more data becomes available and user feedback is gathered, the model can be retrained and refined to increase its accuracy and adaptability. Regular updates and improvements to the model can ensure that it stays relevant and effective in a dynamic hospitality industry.

These future scopes present exciting opportunities to enhance the hotel-image classification model and its application. They can contribute to improved user experiences, more accurate recommendations, and greater personalization in the hotel selection process.

Conclusion

In this study, we compared the performance of a custom CNN model with four pretrained models (ResNet, AlexNet, MobileNet, and VGG16) on a hotel images dataset. The custom CNN model, which consisted of multiple convolutional and fully connected layers, demonstrated superior performance in terms of both accuracy and F1-score.

After training the models for 20 epochs, the custom CNN model achieved an accuracy of 93.86% on the test set, outperforming the pretrained models. Similarly, the custom CNN model attained an F1-score of 0.9403, indicating its ability to capture intricate patterns and make accurate predictions on the different hotel room categories.

These results highlight the importance of designing a model architecture tailored to the specific task at hand. By leveraging the depth and complexity of the custom CNN model, we were able to achieve better performance compared to the pretrained models, which were originally trained on a different dataset.

Further analysis could involve fine-tuning the pretrained models on the hotel images dataset to potentially enhance their performance. Additionally, conducting experiments with different hyperparameters, such as learning rate and batch size, might yield further improvements in model performance.

Overall, this study demonstrates the efficacy of a well-designed custom CNN model in image classification tasks, specifically in the context of hotel room categorization. The findings emphasize the importance of considering both model architecture and dataset characteristics when developing deep learning models for image classification.

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Part B

Individual Contributions

Problem statement: 1. Data Collection and Preprocessing

2. Model development

Name of the student: Sahil Vakkani

- Collect a large dataset of hotel images with labels for different categories such as lobby, guest room, restaurant, pool, etc. This dataset will be used for training and evaluating the model.
- Preprocess the dataset by resizing the images to a consistent resolution, normalizing pixel values, and applying any necessary transformations or augmentations. Split the dataset into training and testing subsets.
- Trained and fine tuned resnet model

Problem statement: 1. Model Selection and Performance Testing

2. Model development

Name of the student: Vidushi Sharma

- Select different image classification algorithms, such as Convolutional Neural Networks (CNNs), and test their performance on the hotel image dataset.
- Evaluate the effectiveness of each algorithm by measuring metrics like accuracy, precision, recall, and F1 score on the test dataset.
- Choose the most effective algorithm based on its performance metrics.
- Trained and fine tuned alexnet model

Problem statement: 1. Model Development and Training

2. Model development

Name of the student: Venkatesh Shirbhate

- Based on the selected algorithm and feature analysis results, develop a model architecture suitable for hotel image classification.
- Train the model using the preprocessed dataset, considering the appropriate loss function, optimizer, and learning rate.
- Monitor the training process and adjust the hyperparameters if needed to improve model performance.
- Trained and fine tuned VGG16 model and MobileNet.

Problem statement: 1. Model Deployment and Application

2. Model development

Name of the student: Adnan Nazmuddin

- Once the model achieves satisfactory performance, deploy it to a production environment where it can be used to classify hotel images into different categories.
- Develop a user-friendly interface or application that allows users to upload hotel images and receive predictions for the corresponding categories.
- Continuously monitor and evaluate the model's performance in the real-world application and make improvements as necessary.
- Trained and developed custom model

Project to Outcome mapping

1. Data Collection and Preprocessing:
The first objective in the machine learning workflow was to collect and preprocess the data. This involved gathering relevant data from various sources, such as databases, APIs, or scraping websites. The collected data was cleaned, filtered, and transformed to ensure its quality and suitability for training the model.

2. Model Development and Training:
Once the data is collected and preprocessed, the next objective was to develop and train the machine learning model. This involved selecting an appropriate algorithm or model architecture based on the problem at hand. The model is then trained using the collected data, where it learns patterns and relationships to make predictions or classify new instances.

3. Model Selection and Performance Testing:
After training multiple models with different algorithms or architectures, the next objective was to select the best-performing model. This was determined by evaluating their performance on a separate dataset called the validation set. Various metrics, such as accuracy, precision, recall, or F1 score, was used to assess the model's performance. The model with the highest performance on the validation set was selected for further deployment.

4. Model Deployment and Application:
The final objective was to deploy the selected model into a production environment where it can be utilized for real-time predictions or applications. This involved integrating the model into a software system or creating a standalone application that can take input data and generate predictions or insights. It is important to consider factors like scalability, security, and efficiency during the deployment process to ensure the model performs well in a production environment.

Sr. No.	PRN No.	Student Name	Individual Project Student Specific Objective	Learning Outcomes mapped (To be filled by Guide)
1	1032190097	Adnan Nazmuddin	Model Deployment and Application	
2	1032190785	Venkatesh Shirbhate	Model Development and Training	
3	1032191630	Sahil Vakkani	Data Collection and Preprocessing	
4	1032191366	Vidushi Sharma	Model Selection and Performance Testing	