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Developing an artificial intelligence framework for online destination image photos identification

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A R T I C L E I N F O

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A B S T R A C T

With the development of advanced technologies in computer science, such as deep learning and transfer learning, the tourism field is facing a more intelligent and automated future development environment. In this study, an artificial intelligence (AI) framework is developed to identify tourism photos without human interaction. Adopting online destination photos of Australia as a data source, the results show that the model combining a deep convolutional neural network and mixed transfer learning achieved the best image identification performance. This study identified 25 image classification categories covering all the tourism scenes to serve as a foundation for future tourism computer vision research. The results indicate that the AI photo identification framework is of great benefit for the understanding of projected destination images and enhancing tourism experiences. This study contributes to the existing literature by introducing an intelligent automation framework to big data research in the tourism field, as well as by advancing innovative methodologies of online destination image analysis. Practically, the proposed framework contributes to the marketing and management of smart destinations by offering a state-of-the-art data mining method.

1. Introduction

The future of global tourism will be strongly influenced by numerous technological advances and tools such as digitization, information and communication technology, machine learning, robotics, and artificial intelligence (AI), which are also driving tourism to face a more automated future (Buhalis, 2020; Tussyadiah, 2020). Today, destinations are challenged to discover new approaches to enhance tourist experiences and adopt effective marketing strategies to build strong destination brands (Li, Robinson, & Oriade, 2017). AI mimics human intelligence, thereby allowing computers to perform human-like work and improving the efficiency of many jobs (Huang & Rust, 2018). In the tourism industry, including hotels, airlines, restaurants, and tourism attractions, the use of AI is becoming popular in practice. New technologies in the domain of AI, such as face recognition, virtual reality (VR), and robots, are helpful for the delivery of a novel on-site experience to tourists (Wang, Xie, Huang, & Morrison, 2020). As tourism inherently involves regular contact with a variety of tourists and produces large amounts of data, the adoption of AI for marketing in the tourism field is crucial.

In the future, dynamic and real-time data mining will be able to facilitate context-based marketing to bring about instant value co-creation (Buhalis & Foerste, 2015). The automation of the frequent real-time measurement and interpretation of large amounts of tourist observational data tied to specific travel motivations will be achieved (Mariani, Mura, & Felice, 2017). Therefore, the regular use of big data will become necessary for smart destination management. In the competitive tourism industry, the concept of AI can enable managers to automate procedures and simplify business activities.

In particular, online photo data constitutes large shares of user-generated content (UGC) data (45%) and big data (21%) (Li, Xu, Tang, Wang, & Li, 2018). Recently, a noticeable trend in tourism marketing is the mainstream transformation of online data from text-based to image-based (Molinillo, Liébana-Cabanillas, Anaya-Sánchez, & Buhalis, 2018). Most of the content posted online is photos (81.2%), followed by links and videos (Mariani, Di Felice, & Mura, 2016). Additionally, photos have been used extensively to promote destinations

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and attractions through visual experiences. Content generated by tourism destination photos greatly influences tourists' perceptions of a destination (Li, Hu, Huang, & Duan, 2017). The adoption of big visual data in smart tourism destination marketing and management is an apparent trend (Wang, Li, & Li, 2013). Photos, as a main type of visual data, have already been adopted in many tourism studies with manual identification methods. AI destination photo recognition can help both industry practitioners and researchers better understand the experiential features conveyed in online destination photos. However, to the best of the authors' knowledge, no existing tourism research has employed photos collected from extensive sources in a smart destination and analyzed by AI technology. Therefore, going beyond the traditional destination studies, this research seeks to address the following question: With the increase of the presence of AI in the tourism field, can an AI framework of destination photo identification be developed for better marketing decision-making?

To answer this question, an advanced online destination photo identification model supported by an AI computer algorithm was developed. This study contributes to tourism big data analysis by using a deep learning method to effectively and accurately analyze online destination photos with little or no human intervention. The empirical results of this study generate an AI system that can mimic human intelligence to accurately identify online destination images. The obtained destination images supported by this technique can assist in tourism policymaking, the facilitation of travel decision-making, and the promotion of destination marketing. This research has a profound influence on improving the effectiveness of the extraction and integration of destination information packets to support tourism marketing decisions, e.g., understanding which types of market segments to target, deciding what kind of preferred marketing communication combination to adopt, and determining how to shape the images of tourism products.

2. Literature review

2.1. Big data studies in destination management

The rise of tourism big data has been induced by increasing data storage capabilities and computational processing power, as well as the increased availability of large volumes of data (Najafabadi et al., 2015). Characterized by significant volume, velocity, variety, and veracity (Song & Liu, 2017, pp. 13–29), tourism big data analysis is strongly related to smart destination management (Li, Hu, et al., 2017) by offering information to support tourism planning and decision-making (Wang et al., 2013).

In today's digital age, data posted and spread online, especially images, have substantial influences on different aspects of the intelligent configuration of destinations (Ivars-Baidal, Celdrán-Bernabeu, Mazón, & Perles-Ivars, 2019). The available information enables considerable advancement toward more location-based marketing (Buhalis & Foerste, 2015). Data provide information anytime and anywhere with the potential to influence the integral travel process, ranging from planning, booking, to experiencing and sharing (Vu, Luo, Ye, Li, & Law, 2018).

The research materials of tourism big data include textual content and multimedia content (e.g., images, videos, audio) from a multiplicity of sources (e.g., Destination Management Organizations (DMOs), social media) (Fuchs, Höpken, & Lexhagen, 2014). Li and Law (2020) pointed out that many previous tourism big data studies focused on textual content, and there is a strong call for research that adopts photos as a data source. The big data adopted in the tourism field are mainly derived from three sources, namely users, devices, and operations (Li et al., 2018). The arrival of AI in the tourism destination system, in which machine learning techniques and neural networks are especially important, has provided new methods for data analysis, data sharing, and data compilation in the tourism field (Tussyadiah, 2020).

Regarding research methods, the application of AI in tourism is expected to increase in the new era (Song & Liu, 2017, pp. 13–29; Tussyadiah, 2020). As a subfield of AI, machine learning applies statistical methods to recognize meaningful patterns from a set of data without human instruction, and it has already been adopted in tourism photo analysis. For example, Deng and Li (2018) used a machine learning model to help DMOs with destination photo selection. Ma, Xiang, Du, and Fan (2018) examined the extent to which online images of hotels influence customers' perceived helpfulness of online reviews by applying deep learning techniques. Zhang, Chen, and Li (2019) sorted the contents of photos into 11 categories and 103 scenes via a machine learning model. However, one prominent problem is that the contents and structures of reviews can be considerably different depending on specific algorithms and the platforms on which AI tourism research is based.

2.2. Study of AI in tourism

AI is derived from information technology and is often used interchangeably with notions such as automation or robotization in tourism (Li, Bonn, & Ye, 2019; Tussyadiah, 2020). Concepts of automation, as well as AI, define the future of smart tourism from the perspective of tourism destinations (Li, Hu, et al., 2017). AI affords unprecedented opportunities for the development of automated systems for tourism planning, marketing, and management (Buhalis & Sinarta, 2019). Previous research on AI in the tourism field has primarily focused on two research areas, namely the design of useful AI programs and the evaluation of the impacts of AI on tourism.

Regarding the design and delivery of AI systems, many prior studies have shed light on text recognition (Ma et al., 2018), decision-making (Law, Li, Fong, & Han, 2019), robot automation (Ivanov & Webster, 2020), and image recognition (Ren, Vu, Li, & Law, 2020; Zhang et al., 2019). Previous research has processed machine learning and data analytics to complete descriptive and predictable tasks in the tourism field with pre-training models borrowed from other disciplines. Thus, these frameworks have limitations, and the results must be adjusted to the adopted model. However, these limitations can be overcome by introducing more specific and precise AI technology to the tourism field.

In recent years, some studies have explored the range of the impacts of AI on the tourism industry and society, or, more specifically, on tourists and employees. For example, as AI can drive robots to accomplish human-like tasks, Li et al. (2019) investigated the impacts of hotel robotics and how robots influence the behaviors and attitudes of employees in the hospitality industry. Murphy, Gretzel, and Pesonen (2019) conceptualized the impact, range, and role of anthropomorphic characteristics in automation service experiences. From the perspective of guests and hoteliers, Choi, Choi, Oh, and Kim (2020) demonstrated the effects of human–robot interaction. Evaluating these impacts provides new ways of measuring AI performance in the tourism sector. In the future, more research should be undertaken to explore accurate approaches that capture the full benefit of automation to optimize the impacts of automation governed by AI and apply it in practice. In this study, state-of-the-art AI technology is utilized, which meets the requirements for designing viable AI systems for tourism.

Moreover, some scholars have proposed four types of AI in the management context, namely mechanical AI, analytical AI, intuitive AI, and empathetic AI, based on the different capabilities of AI to replicate human skills (Huang & Rust, 2018). Many existing tourism studies have concentrated on mechanical AI, which copes with simple and repetitive tasks. Looking to the future, analytical AI can iteratively learn data via the use of algorithms and can process information for problem-solving with intelligently analytical skills (Tussyadiah, 2020). Machine learning is the major application of analytical AI. In the field of destination management, there is a lack of research on systematic AI analysis for both user-generated photos posted by tourists and official photos on government and business websites; this is due to the lack of mature approaches that can effectively identify tourism photos in the context of big data. As such, this paper develops a framework for the AI identification of online tourism photos and illustrates the experimental process by which to validate its performance to facilitate the automatic analysis of photo contents.

2.3. Tourism destination image photo analysis

Tourism researchers use photos as data to understand how visual images represent and shape a destination (Stepchenkova & Zhan, 2013). Destination photos shape and re-shape travelers' perceptions of the locations (Marine-Roig & Clavé, 2015). There are two main components of an image, namely the content and the composition. The content includes the totality of its appearance, while the composition refers to the way in which the appearances are combined in relation to other appearances (Albers & James, 1988). In the field of tourism, empirical studies that have used photos as data can be divided into two major groups according to the emphasis of the research (Balomenou & Garrod, 2019). The first group comprises those studies in which a sample of found images is used to research conclusions about the nature or characteristics of the destination image. The analytical treatment of photos may include semiotic analysis and content analysis (Kim & Stepchenkova, 2015).

The second group of studies employs photos to gain an understanding of tourists' experiences and behaviors at a destination (Salas-Olmedo, Moya-Gómez, García-Palomares, & Gutiérrez, 2018). These studies use geotagged images as a data source, in which metadata is embedded (e.g., the time, location, etc.), as well as text affiliated with the images (e.g., a tag, title, description, etc.) (Deng & Li, 2018; Zhang et al., 2019). The adoption of statistical and ArcGIS spatial methods to analyze geotagged photos in different cities and regions can help to determine the attractiveness of tourism sites (Giglio, Bertacchini, Bilotta, & Pantano, 2019) and understand tourists' travel behavior patterns (Vu, Li, Law, & Ye, 2015; Zhang et al., 2019). However, geographic attributes only function as a symbol or a background of a destination in an image, whereas visual content with features in an image can provide more information about a location. A combination of visual features that shape the framed image as a whole, namely the photographic content (e.g., color, shape, texture, light, and composition), can help the researcher achieve a more thorough understanding of the overall scenes of images. Photo contents themselves incorporate a wealth of valuable information in addition to the metadata (Nikjoo & Bakhshi, 2019), and powerful data mining techniques that can act directly on the contents of images are therefore required.

The current photo analysis methods in tourism research face several critical limitations. First, the analysis of destination photos traditionally relies on social science disciplines because of the source of both supporting tools and theory of inquiry (Park & Kim, 2018). In previous studies, analysis has been undertaken primarily by using manual approaches. There is no existing method that can help tourism researchers and practitioners systemically and automatically recognize destination photos systemically and automatically. Given its methodological nature, the identification of the contents of images via visual narratives demands a high level of involvement of researchers. The subjective nature of data interpretation raises the serious issue of ambiguity in manual data processing. Machine learning will be a suitable way to deal with large volumes of data and to remove human intervention (Ma et al., 2018).

The second limitation of tourism photo research is the small size of the photo data (Hao, Wu, Morrison, & Wang, 2016) and the low efficiency of data mining (Lu & Stepchenkova, 2015). In today's era of big data, there is a tremendous number of existing images, and the raw data are often in an unconstructed format with poor quality. As new photos are constantly being generated, there is a need to create a high-performance model to improve the efficiency of tourism big data processing.

Third, a more crucial issue of content analysis is related to the classification of photos. Creating certain protocols in categorization of photo is the foremost step in the AI image identification process (Lecun, Bengio, & Hinton, 2015). Applications of image identification in other fields often involve specific types of images, such as license plate images, medical images, and fruit images. However, the diversity of the contents represented in tourism images is the barrier to the application of computer vision in tourism. Therefore, the content analysis of image descriptions requires nonspecific levels and generic image categories. This research area is overlooked in tourism photography, and should be dealt with via advanced data mining techniques.

3. The development of an AI framework of online destination photo analysis

This section demonstrates the process of the AI analytical approach in dealing with online tourism photos. Compared with traditional methods, the proposed novel approach minimizes the requirement for human visual inspection, increases the quality of the resulting photos, enables near-real-time discovery, and significantly reduces the cost.

3.1. Data sources and data collection

In this study, online destination photos of Australia geared toward the Chinese tourist market were used as a case study to conduct the proposed AI deep learning analysis. Official tourism websites provide authoritative information to tourists, and the photos hosted on these websites are often of better quality. The official websites of Tourism Australia, Tourism Western Australia, Tourism Victoria, Tourism Queensland, and Tourism New South Wales were selected as the main data sources. Deep learning requires a large quantity of data for training. To obtain more images to achieve better results, relevant online images from the websites of nine major Chinese online tourism agencies (OTAs), such as Ctrip and Tuniu, were also selected to supplement the tourism photos.

The photos on the abovementioned from these data source websites were automatically crawled using a self-designed Python crawler program. The crawler chose photos from these 14 websites and downloaded them. After the photo collection was completed, it was necessary to check the quality of all the downloaded photos. There are two types of quality problem. First, some photos could not be displayed due to network instability, photo path errors, and other problems that made the required information unavailable. These photos were useless data and python programming was used to determine whether the picture is a valid picture. The invalid pictures were deleted. Second, a lot of advertising data that is irrelevant to tourism destinations may exist in the pictures of the OTA websites. Python programming was employed to analyze whether the text description associated with a picture is related to tourism destination. The irrelevant pictures were also removed.

In this study, the perceptual hash algorithm was used to extract the image features and remove the weights of all the collected photos. The Hamming distance, which is the number of data bits between two images, was used to eliminate highly repetitive images. It is an important index for the determination of the similarity between two images; the smaller the Hamming distance, the greater the similarity (Rai & Yadav, 2014). The Hamming distance between two images was calculated from the hash values of the images, and if it was less than 5, the two images were considered to be the same (Norouzi, Fleet, & Salakhutdinov, 2012). Ultimately, 30,951 valid images were obtained after the invalid, unrelated, and repetitive images were removed. The distribution of the number of photos in the 14 sources are displayed in Table 1.

3.2. Data annotation

Photo classification was conducted via data annotation using deep learning, a method that simulates the complex hierarchical cognitive pattern of the human brain, thereby narrowing the gap with the visual system of the human brain and endowing the machine with the ability to

Table 1
Photo sources.

Type of website	Name of website	Number of photos
Official websites	Tourism Australia	**1018**
	Tourism Western Australia	**6949**
	Tourism Victoria	**669**
	Tourism Queensland	**5081**
	Tourism New South Wales	**2145**
Online tourism agencies (OTAs)	Ctrip	**6497**
	Tuniu	**2185**
	iTrip	**543**
	Toursforfun	**1314**
	Lulutrip	**1352**
	Spring Tour	**572**
	Aoyou	**531**
	TripAdvisor	**1843**
	China Travel Service	**252**
Total		**30,951**

extract concepts. After data preparation, it was necessary to label each photo for classification; it was stipulated that each image would have only one label. Before the images could be annotated, an annotation system was established. The main class categories were established based on the six commonly recognized domains of tourism based on previous literature (Leiper, 1979; Mak, 2017; Zhai, 2006), namely food, accommodation, transport, sightseeing, shopping, and recreation. These six domains cover the basic elements of tourism (Leiper, 1979; Zhai, 2006). Based on research by Mak (2017) and Vu, Li, Law, and Zhang (2018), the tourism photos were then further divided into 25 sub-class categories.

The classification framework used by Mak (2017) appeared to be too complicated to be adopted in this study. Therefore, the framework was simplified by taking into consideration the nature of the photos in this study. For example, limited imaged data were collected in the category of ‘traffic’. Therefore, the sub-categories of ‘air transport’, ‘land transport’, and ‘maritime transport’ were defined. It was also found that many of the collected images were related to accommodation; hence, these images were further divided into six sub-classes. As tourism activities using recreational vehicles (RVs) are popular in Australia, after reviewing a sufficient number of RV-related images, ‘RV’ was designated as a sub-category. In addition, as Australia is famous for wine tourism and the coffee industry (Hojman & Hunter-Jones, 2012), ‘wine and coffee’ was designated as a sub-category for photos related to wine culture and coffee. Skydiving and hot air ballooning are also very distinctive recreational activities in Australia; thus, based on the nature of these activities, images depicting these two activities were placed in the category of ‘aerial recreation’, while photos of other recreational activities were placed in the category of ‘recreation except aerial activities’. The classification scheme is presented in Table 2.

To effectively carry out the manual image data annotation, an image labeling program was designed and developed for assistance. The Python Flask framework was adopted in the program so that several people could use it online at the same time. The researchers assessed the content of each photo and assigned it to one of the categories listed in Table 2. The corresponding selection was made using the program interface. After assessing and selecting a batch of images, the photos assigned to the different categories were moved to the image directories corresponding to the categories, and, after confirmation of the submissions, the labeling of the batch of photos was completed.

3.3. Data processing

As manual labeling will inevitably involve human error, it is necessary to check the quality of labeling. Thus, an image quality audit platform was set up using the Python Flask framework. Several assistant auditors identified any incorrectly classified photos and relabeled some photos to place them in the category of ‘other’. Via continuous annotation and checking, the classification of image categories was completed as accurately as possible to provide high-quality data sets for model training.

Table 2
Photo classification system.

Main categories	Sub-categories	Range of labeling
Food	1.Staple food	Seafood dishes and their raw materials, Western cuisine and other cuisines
	2. Dessert	Ice cream, chocolate, cake, macarons, milkshakes
	3. Fruits and vegetables	Fruits and vegetables, fruit platters and salads, fruit and vegetable picking
	4. Wine and coffee	Wine, beer, cocktails, coffee
Accommodation	5. Indoor accommodation area (with bed)	Accommodation space with bed
	6. Indoor non-accommodation area (without bed)	Living room, kitchen, sofa desk and chair, hotel hall, conference room, bathroom
	7. Recreational vehicle (RV)	Only photos of RV exteriors included
	8. Outdoor scenes	Views outward from interiors and including a building element, such as a balcony
	9. Surrounding environment of accommodation	Full views of hotels and housing accommodation, overhead views of surrounding environment and accommodation area
	10. Accommodation facilities	Swimming pool, fitness equipment, billiards, badminton court
Traffic	11. Maritime traffic	Cruises, sailboats, yachts
	12. Land transportation	Trains, passenger cars, off-road vehicles, cars
	13. Aerial traffic	Helicopters, passenger planes, cable cars
Sightseeing	14. Mountain tours	Mountains, hilly terrain, rocks, caves
	15. Land sightseeing	Deserts, rainforests, plants, streams, parks
	16. Water sightseeing	Rivers, lakes, seas, beaches, coastlines
	17. Water sport activities	Experience of sport activities such as jet skis, rubber boats, skateboards, water surfing
	18. People and animals in water	Diving, whale watching, aquariums, sea fishing, water animals
	19. Scenes involving land animals	Interactions between land animals, interactions between humans and land animals
	20. Scenes involving aerial animals	Interactions between animals in air, interactions between humans and animals in air
	21. Buildings	Landmark buildings and urban buildings with sightseeing appeal
Shopping	22. Shopping malls with people	Small fairs, exhibitions, shopping malls, shopping scenes in which people appear
	23. Shopping malls without people	Scenes in which there are no people but rather only goods, shop scenery, and/or shop signs
Recreation	24. Recreation except aerial activities	Recreational activities on land and other places, such as skiing, sand skiing, golf, etc.
	25. Aerial recreation	Skydiving, hot air balloons, bungee jumping equipment, and other amusement items

The images were digitalized, the color spaces were converted, and the data were standardized to facilitate the deep learning model to extract features from the photos and improve the accuracy of photo identification. Python programming and the tf.keras model in TensorFlow were used in the backend of the deep learning framework.

As the number of input nodes of the neural network is fixed, the size of every photo input to the neural network should be the same. The convolutional neural network (CNN) model was adopted to test the photos of different sizes, and the size of 224 × 224 was found to be appropriate. Therefore, all the photos were adjusted to a size of 224 × 224 and standardized accordingly. As a result, different features of the photos (such as the size and color) had the same scale. After each photo was digitized, the values in the three-dimensional array of the photo were between 0 and 255. These values were divided by 255 to normalize them to a value between 0 and 1. This is a typical processing method for the deep learning of photo identification. During the training process of the neural network, the convergence of the weight parameters was accelerated to improve the training efficiency.

After the previously described processing was completed, the data set was divided into a training set and test set; 70% of the photos were randomly selected as the training set, while the other 30% were used as the test set.

3.4. Classification model based on mixed-model transfer learning

The conventional CNN model is not ideal because its image classification accuracy is less than 0.7(Jiang & Learned-Miller, 2017), which is not adequate for application purposes. Theoretically, the accuracy of a CNN model can be improved by increasing the number of images used during training. However, for specific projects that are limited by experimental conditions, it is difficult and time-consuming to optimize this process. Another technical method, namely transfer learning, was therefore employed to improve the efficiency of the CNN model.

3.4.1. Transfer learning

The ability to transfer knowledge to a new environment is often called transfer learning, the basic concept of which is to map the source and target dataset images into a high-dimensional subspace. In this subspace, the distributional difference between the target datasets and image sources is reduced. In transfer learning, a small sample of the data is used as the target domain, and a large number of labeled data sets is used as the source domain. In this study, the natural image dataset 'ImageNet' was used as the source domain, while the collected images were used as the target domain. As most of the online destination photos were natural photos and had certain similarities with the source data set, good classification results could be obtained.

The construction of a CNN has a significant influence on the experimental results. Based on the training data, model parameters, and hardware conditions, the data collected in this study were used to conduct several computer experiments, and the results were compared. To achieve high accuracy, the Densenet169 model was selected to construct the network using transfer learning methods.

$$\text{Precision} = \frac{\text{Correct number of samples in a specific category after prediction}}{\text{Number of samples in a specific category after prediction}} \tag{1}$$

In the experiments conducted in this study, applications of the tensorflow.python.keras module were used to construct DenseNet networks. DenseNet169 obtained better results when the photo size was 224 × 224. Moreover, improving the image resolution was not a feasible approach to further improve the image classification accuracy. Therefore, two transfer learning methods were combined to improve the effect of image classification, as subsequently described.

3.4.2. Photo classification model based on mixed transfer learning methods

The transfer learning approach significantly reduces the amount of training data needed to achieve the required performance for the design of viable AI systems for tourism. The concept of transfer learning is that the knowledge learned from one task can be applied to solve other similar problems; thus, researchers can save a significant amount of time during model training. There exist several transfer learning methods, including DenseNet and Xception. In this study, transfer learning was primarily based on feature representation, i.e., learning a good feature representation through a source domain, encoding knowledge in the form of features, and transferring the knowledge from the source dataset to a target dataset to improve the target dataset/task effect. The basic principle of mixing is to obtain more feature representations. Based on the previous analysis undertaken in this study, DenseNet can be considered a good transfer learning method. Xception was also chosen due to its good performance in the classification of tourism images. The network structure after mixing is presented in Fig. 1.

As shown in the first row of Fig. 1, the input image data were expressed in a 224 × 224 × 3 format, where 3 represents the color channel (RGB) and 'None' denotes the batch, and its size was set during the training. The second and third rows respectively represent two transfer learning methods, namely DenseNet169 and Xception(Chollet, 2017). These are followed by global pooling and global average pooling, which were then concatenated to establish the output of the 25 sub-categories.

4. Experimental results

The results of different methods were compared, and it was concluded that the transfer learning approach combined with DenseNet169 and Xception was the more suitable approach for this domain, as it yielded the best accuracy, the shortest training time, and less overfitting with small datasets.

The batch size was set to 10. After 50 iterations, the accuracy of the test data set was 85.1% and the average iteration time was 17 min. According to the experimental results, the accuracy of the mixed transfer learning technique was approximately 4% higher than that of the simple transfer learning method, which is considered a substantial improvement.

Not only was the overall accuracy of the classification model of concern, but the classification ability of the model for each sub-category was also investigated. Table 2 presents the evaluation index values of image classification. The test results are reported in terms of precision (P), recall (R), and an F_1 parameter. The P-value represents the true ratio of samples belonging to the sub-category. The R-value represents how much of the true content of this sub-category was correctly predicted. The F_1-value can be considered as the weighted sum of precision and recall.

$$\text{Recall} = \frac{\text{Number of samples in a specific category after prediction}}{\text{Number of all samples}} \tag{2}$$

$$F_1 = \frac{2 \times \text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} \tag{3}$$

As reported in Table 3, photos of 'aerial recreation' and 'indoor accommodation area' had the best classification results, with F_1-values reaching 96%. However, the classification of 'buildings' images had the poorest prediction accuracy with an F_1-value of 72%. Table 4 presents sample photos of the five classes with the best evaluation effects and the

Layer(type)	Output shape	Param #	Connected to
input_1(InputLayer)	[(None,224,224,3)	0	
densenet169(Model)	(None,7,7,1664)	12642880	input_1[0][0]
xception(Model)	(None,7,7,2048)	20861480	input_1[0][0]
global_average_pooling2d(Globa	(None,1664)	0	densenet169[1][0]
global_average_pooling2d1(Glo	(None,2048)	0	xception[1][0]
concatenate(Concatenate)	(None,3712)	0	global_average_pooling2d[0][0] global_average_pooling2d-1[0][0]
dense(Dense)	(None,512)	1901056	concatenate[0][0]
dropout(Dropout)	(None,512)	0	dense[0][0]
dense_1(Dense)	(None,25)	12825	dropout[0][0]

Total params:35,418,241
Trainable params:35,205,313
None-trainable params:212,928

Train on 21677 samples, validate on 9274 samples

Fig. 1. Transfer learning model based on mixing of DenseNet169 and Xception.

five classes with the worst evaluation effects.

Differences in the photo contents were found to contribute to the distinction between the best-predicted and worst-predicted categories. As shown in Table 4, in the categories with a poor classification effect, the exterior features of buildings and architecture are similar, so they interfered with each other and created challenges in distinguishing one from the other. In photos of shopping malls, people in the photos tend to appear small, causing false identification. In addition, the contents of 'land sightseeing' photos are quite extensive, ranging from deserts and rainforests to plants, streams, and parks, making it difficult to distinguish them from other categories. In contrast, in the 'aerial recreation' sub-category, the aerial elements in the photos are very noticeable, so they were easy for the computer to recognize. It was therefore easier to distinguish between categories that exhibited greater differences.

5. Discussion

A tourism-based deep learning model was developed for mining the extensive amount of destination photos; in the future, this model can be capable of specifically and precisely analyzing millions, or even billions, of newly collected destination photos. The proposed machining learning model transforms useful and relevant visual data into information blended with the tourism context, thereby developing foundational knowledge to leverage AI for destination management. From the results, the optimum implementation of this AI approach can be applied from two perspectives, namely the identification of projected destination images and the enhancement of tourism experiences.

On one hand, projected online destination images, namely the attributes projected through marketing communications that represent the typical characteristics of tourism products (Hunter, 2016), are understood automatically. It was found that the images of one destination (Australia) projected to its important tourism-generating country (China) include nothing more than the 25 identified sub-categories. Concerning categorization, the content of photos is an essential issue that must be understood before projecting an image of any destination (Mak, 2017; Picazo & Moreno-Gil, 2019). From data to action, tourism practitioners can use the results of this study as a basis for computer-aided destination image identification in fields such as personalization and predictive behaviors (related to customer behaviors), as well as segmentation and analytics (linked to marketing strategy). The various elements of a destination are the combined product of government authority and private commercial efforts.

The use of AI photo identification enables comparative evaluations to maintain concordance between the projected images and destination marketing strategies. Traditional destination image identification has been previously performed by researchers and relies on subjective judgments (Mak, 2017; Stepchenkova & Zhan, 2013), which may require a heavy cognitive burden and a considerable processing time to search and select information from among thousands of photos. In the big data era, smart destinations could be considered as massive data generators (Li, Hu, et al., 2017) and online tourism photos are created every moment of every day; therefore, human-based identification is unfeasible in such cases. Hence, automated photo analysis can be beneficial to address these issues, and this study provided 25 standardized criteria for understanding the contents of projected destination images, thereby serving as a tool that can help transform and improve the destination.

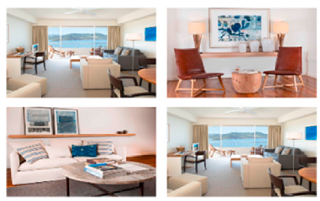
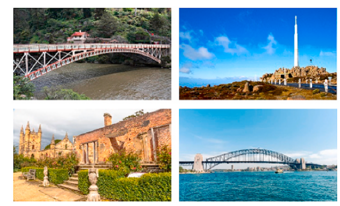
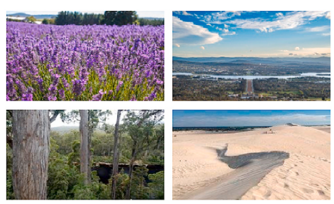
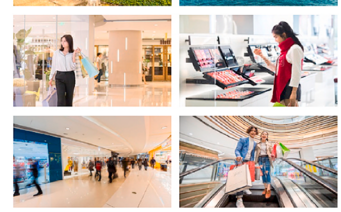
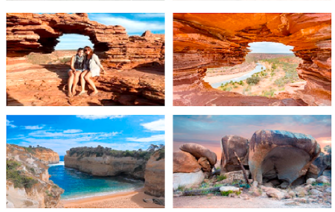
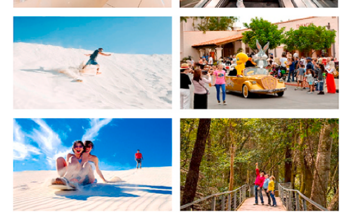
The websites of tourism destinations provide detailed information about the tourism services and products of the location. By identifying the contents of images through this AI model, tourism service providers can collect location-based information about the preferences and needs of customers to deliver personalized recommendations in real-time. The greatest advantage of personalization as experienced by tourists is an increased satisfaction level with obtaining services in a desired way (Buhalis & Sinarta, 2019). Photo content generated online has an important influence on customers' attitudes, as well as their behavioral intentions in a destination (Trunfio & Campana, 2019). Automatic photo identification assists in real-time marketing and supports dynamic marketing and flexible service offerings, which can support destinations to enhance their overall competitiveness.

On the other hand, tourism also experiences changes due to intelligent automation in relation to the timely identification of context-specific activities, such as dining, recreation, and points of interest. Based on the analysis procedure proposed in this study, the applications of automation in tourism could be mapped into the tourism experience. Destination photos provide the tourist with information that can be combined with other factors related to the tourist experience. As a component of "electronic word of mouth" (eWOM), the contents of destination photos are closely related to the experiences of tourists at tourism attractions (Wang, Hao, Law, & Wang, 2019). The proposed AI

Table 3
Photo classification results.

Ranking according to evaluation index	Sub-categories	P-value	R-value	F_1-value
1	Aerial recreation	0.98	0.95	0.96
2	Indoor accommodation area (with bed)	0.96	0.96	0.96
3	Aerial traffic	0.97	0.93	0.95
4	Scenes involving aerial animals	0.96	0.93	0.95
5	Indoor non-accommodation area (without bed)	0.94	0.89	0.91
6	Recreational vehicle (RV)	0.89	0.93	0.91
7	Scenes involving water animals	0.93	0.88	0.90
8	Fruits and vegetables	0.87	0.93	0.90
9	Maritime traffic	0.85	0.92	0.88
10	Staple food	0.88	0.87	0.87
11	Dessert	0.87	0.87	0.87
12	Wine and coffee	0.87	0.86	0.87
13	Scenes involving land animals	0.87	0.86	0.86
14	Water sightseeing	0.84	0.84	0.84
15	Accommodation facilities	0.86	0.83	0.84
16	Land transportation	0.85	0.79	0.82
17	Water sport activities	0.82	0.79	0.80
18	Shopping malls without people	0.77	0.84	0.80
19	Surrounding environment of accommodation	0.77	0.81	0.79
20	Outdoor scenes	0.80	0.76	0.78
21	Recreation except aerial activities	0.76	0.79	0.77
22	Mountain tours	0.76	0.75	0.76
23	Shopping malls with people	0.74	0.76	0.75
24	Land sightseeing	0.74	0.75	0.75
25	Buildings	0.71	0.73	0.72

Table 4
Sample photos of the 5 best and 5 worst sub-categories.

Best 5 sub-categories	Sample photos	Worst 5 sub-categories	Sample photos
Aerial recreation (F_1 = 0.96)		Buildings (F_1 = 0.72)	
Indoor accommodation area (with bed) (F_1 = 0.96)		Land sightseeing (F_1 = 0.75)	
Aerial traffic (F_1 = 0.95)		Shopping malls with people (F_1 = 0.75)	
Scenes involving aerial animals (F_1 = 0.95)		Mountain tours (F_1 = 0.76)	
Indoor non-accommodation area (without bed) (F_1 = 0.91)		Recreation except aerial activities (F_1 = 0.77)	

system incorporates different types of context-aware deep learning and transforms them into essential elements for supporting the development of new visitor experiences. AI and real-time big data mining identify what really matters at every particular moment. If applied at a stage before a trip, intelligent automation, such as the proposed model, can provide travelers with inspiration and assist them in the experiences of information searching and pre-arrival image-building.

Moreover, automatic photo identification provides technical support in the creation of virtual destinations for marketing. It should be noted that VR technology today, by providing VR previews of destinations and their facilities, offers infinite potential for widespread virtual visitation to real tourism destinations. The visual elements generated from this research can help the tourism industry provide positive virtual experiences to their customers. For example, through the analysis of millions of photos, all the visual elements of the Great Barrier Reef related to tourism can be identified, including the scene of the Great Barrier Reef and also tourism-related activities; Then, three-dimensional virtual scenes resembling real-life situations can be established. Tourists can actually feel and experience the excitement just like in a real trip. Effective photo identification leads to high level of perceived authenticity of VR content, which provides co-creation value in visitors' pre-, onsite, and post-visit experiences (Kim, Lee, & Jung, 2020).

6. Conclusion, contributions, and future research

The present study makes several contributions to existing tourism academia and practice. First, it distinguishes the characteristics of destination photos and contributes to the body of tourism knowledge. For the content analysis of tourism photos, 25 categories that were believed to reflect all the essential characteristics of the image of a destination were developed. Unlike previous studies that relied on a single data source (e.g., Flicker, Facebook) (Deng & Li, 2018; Ma et al., 2018; Stepchenkova & Zhan, 2013; Zhang et al., 2019), this study utilized photos from a variety of websites. An exhaustive search was conducted to obtain a photo pool that was representative of all types of tourism photos. The elements of destination photos were comprehensively covered from the aspects of food, accommodation, traffic, sightseeing, shopping, and recreation. This provided synthetic representations of data suitable for AI analysis and enabled the automated identification of photos, without requiring human intervention, which is the ultimate goal of AI.

Specifically, this study enables the theoretical development of research related to online photos analysis in the tourism field. During the process of categorization, a set of categories by which the patterns or the meanings behind photos can be discovered was encoded to classify the images. As an important step toward AI, this research introduced a deep learning model for the evaluation of tourism images. The application of this entire procedure to data processing will be the foundation of an intelligent computing module for future studies on tourism photos. This visual data mining model is revolutionary for the tourism industry due to its capability of exploring unknown patterns from massive amounts of data without human intervention. To the best of the authors' knowledge, this is the first approach to automatically consider the visual contents in tourism photos through AI methods. Unlike traditional methods, a massive spreadsheet with features does not need to be created for classification. The AI-based method yields a significantly more consistent performance than any human performance from the perspectives of a fatigue-free performance and a highly reliable response to the environment.

In addition, the study demonstrates the ability of computer AI algorithms to process tourism image identification, which offers a significant methodological contribution. This analysis establishes a foundation for intelligent automation in the tourism industry and employs frontier technology to enhance the analytical capabilities of AI in the tourism field. Deep learning is an advanced technique used in big data solutions for photo recognition (Zhang, Yang, Chen, & Li, 2018) and has become one of the mainstream research topics in the field of machine learning. The developed framework captures a wide variety of unstructured destination images and yields an intelligent analysis. Capable of simulating human intelligence, the proposed method makes good use of state-of-the-art models and advanced AI technology, which enables computers to perform human-like tasks by automatically learning, thereby improving the efficiency of destination image analysis.

Furthermore, several managerial implications can be derived from the findings of this study. Tourism practitioners can benefit from this method to develop AI-assisted decision-making systems to automate online destination management. First, photo identification could enhance the rich content information of destination images. The classification scheme generated by this study covers all scenes of tourism destinations. The most recent photo identification models incorporated with AI are expected to assist in the intelligent decision-making of DMOs and provide the necessary automation processes to support the construction of smart tourism ecosystems.

Second, this paper, in which Australia was adopted as a case study, also makes a best-practice contribution, and the findings related to this big data analytical framework have several potential implications for tourism operations and the service innovation of other destinations. The proposed sophisticated AI photo recognition model could enable tourists to enhance their travel experiences via engagement and process automation, and could also provide information from auto-bookmarked photos.

A few limitations of this study must be noted, and these limitations also indicate future research avenues. First, each unit of content was classified into only one category. However, as photos are complex entities, each photo could be coded into several categories; hence, photos need to be classified into smaller content units. Future studies should focus on multi-object tourism photo identification. As such, the identification of tourism photos contents can involve more possible objects, themes, and scenes. Additionally, in this study, the semantic segmentation of tourism photos by AI deep learning was not conducted. However, semantic meanings are also important features in destination images (Ren et al., 2020). Many elements in tourism such as art, culture and people are mostly represented in the semantic components of photos. Future research efforts may also be directed toward the semantic segmentation of destination images via the use of deep learning, allowing practitioners to effectively recognize all possible semantic elements. Finally, due to the arrival of the fifth-generation (5G) mobile network, short videos also play a vital role in shaping destination images. For instance, one of the most popular Chinese short video applications, Douyin (internationally known as TikTok), has more than 300 million monthly active users (Xiang, 2019). Promotional videos constitute an indispensable tool in identity communication and destination branding, through which knowledge about a destination can be conveyed and an appealing image can be created (Losada & Mota, 2019). Based on the current research findings, further studies can focus on the development of an AI-based model to identify short videos related to tourism.

Author statement

Renwu Wang contribute to the paper by the part of **methodology, software, data curation.** Jiaqi Luo contribute to the paper by **validation and writing-original draft preparation.** Songshan (Sam) Huang contribute to the paper by **conceptualization, writing-reviewing and editing.**

Declaration of competing interest

None.

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