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CASE STUDY: THE CLASSIFICATION OF THE ROOMS IN HOLIDAY HOMES WITH DEEP LEARNING

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ABSTRACT

From reservation to the accommodation process, the effects of technology are increasing day by day in the field of tourism. Online booking platforms, virtual support assistants, mobile applications, and artificial intelligence tools can be given as examples. In the focus on artificial intelligence for tourism, different tools can be presented as examples, especially price analysis regression/recommendations, room, house & amenity classifications from images, and occupancy estimations. Our case study consists of two different steps. First, a dataset was created from a German-based tourism reservation company. In the second step, 5 different deep learning models were trained to compare the accuracy and loss with the dataset. We trained ResNet, DenseNet, VGGNet, Inception v3, and NASNet models. The following accuracies were observed based on 20 epochs of training; ResNet 97.4%, DenseNet 98.69%, VGGNet 97.31%, Inception v3 97.33%, and NASNet 97.21%.

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INTRODUCTION

Tourism is an important area that directly contributes to the economies of various countries and regions around the world. National and international holidays increase accommodation, services, and other activities in tourism destinations. Places such as hotels, holiday homes, etc. can be considered as accommodation options (Martín et al., 2018). As a type of accommodation, holiday homes are in a house or flat or can cover the entire place. Holiday

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homes do not belong to a hotel, and they do not provide services like a hotel. These kinds of accommodations have their own cooking facilities. Generally, holiday homes, are rented by guests for a short period (Scanlon et al., 2014).

When we look at the holiday homes business statistically, the income for 2019 is 57.6 million dollars (Statista, 2019). Moreover, holiday homes are the most preferred holiday plan by European Union (EU) citizens with a rate of 51% (Statista, 2023). Vacation preferences of EU citizens are presented in Table 1.

Table 1. *Distribution of holiday preferences of EU citizens for 2023 (Statista, 2023)*

Holiday Preference	Percentage of the Preference (%)
Holiday Homes*	51
Hotels	47
Bed and Breakfast	15
Camping	10
Boat/Cruise	5
Motor home, Camping Trailer, Mobile Home	5

* The holiday homes percentage includes rental houses, holiday homes friend's/family's houses, or own holiday homes

According to the statistics published by Homeaway, the holiday homes business generated a total net income of 285 million pounds in the UK in 2014. When this revenue is analyzed regionally, London earned 70 million pounds, Cornwall 15 million pounds, and North Yorkshire 9 million pounds net income (Scanlon et al., 2014).

Table 2. *Percentage distribution of holiday home markets in the EU by country (Assa Abloy, 2017)*

Country	Market Distribution (%)
Germany	17.47
France	13.49
United Kingdom	12.91
Spain	10.41
Italy	6.51
Other EU Countries	39.21

According to the research of Assa Abloy (2017), the size of the holiday homes business in the EU is 23.28 billion euros as of 2016 and the estimation for 2023 is reaching 32.5 billion euros. The compound growth rate in this year's range is expected to be 5.8%. 29.3% of bookings are made online and the rest by other methods. The largest holiday home markets in the EU as of 2017 published in Table 2 (Assa Abloy, 2017).

According to data published by the Turkish Statistical Institute (TUIK), the average number of overnight stays in Turkey in 2023 (first three quarters) was 10 nights. Annual tourism revenue is 41.9 billion dollars for 2023, with a total of 44.6 million visitors (first three quarters). Tourism statistics for the last 9 years published by TUIK are given in Table 3 (Turkish Statistical Institute, 2024).

Table 3. *Tourism data from TUIK (*Only the first two quarters provided for 2024)*

Year	Annual Tourism Revenue (Thousand $)	Number of Visitors	The average number of overnights
2015	32,492,212	41,617,530	10.1
2016	22,839,468	31,365,330	11.4
2017	27,044,542	38,620,346	10.9
2018	30,545,924	45,628,673	9.9
2019	38,930,474	51,860,042	9.9
2020	14,817,273	15,826,266	12.4
2021	30,173,587	29,357,463	12.6
2022	46,477,871	51,369,026	10.3
2023	55,874,176	57,077,440	13.3
2024*	23,660,318	25,107,974	11.1
Total	**322,855,845**	**387,830,090**	**11.19 (Average)**

In the past, companies sold holiday packages through various agencies, communicating face-to-face with customers. Nowadays, online reservation is mostly preferred. Customers can find help at the decision stage through personal assistants and Artificial Intelligence (AI) applications used by major booking portals. For offering the best holiday to the customers, these major booking portals use price analysis, location suggestions, date suggestions, and personal offers to the customers. Behind these applications, technologies such as big data, algorithms, deep learning (DL), mobile applications, artificial chat assistants can be found (Zsarnoczky, 2017).

The main objective of this study is to explore the application of DL models in the classification of images related to holiday homes, with the aim of improving the accuracy and efficiency of automated systems in the tourism industry. Specifically, our research aims to achieve the following objectives;

1. Dataset creation: Create, develop and design a unique dataset from a German-based tourism reservation company, ensuring privacy and confidentiality, to allow the training of DL models.
2. Model training and comparison: Train and compare the performance of five popular DL models - ResNet, DenseNet, VGGNet, Inception v3 and NASNet - on the dataset created.

3. Accuracy assessment: Evaluate the accuracy and loss metrics of these models over 20 epochs to determine their suitability for practical applications in the tourism industry.
4. Optimize user experience: Improve the usage of AI and technology in the tourism industry to enhance the experience of both guests and landlords, and to demonstrate possible application perspectives for the industry.

By addressing these objectives, this study aims to contribute to the growing body of knowledge on the use of AI in tourism, specifically in the automated classification of holiday home images. The knowledge gained from this research can contribute to the development of more accurate and efficient AI-based tools for online booking platforms, thus improving the overall customer experience in the tourism sector. Therefore, we performed a case study and focused on the classification results of the five popular DL models with our own created dataset. Our study consists of two different steps. The first step was creating the dataset for this study. The room image data was collected from a German-based tourism reservations company (due to the privacy concerns, researchers are not allowed to expose any data publicly). In step two, using the dataset, ResNet, DenseNet, VGGNet, Inception v3, and NASNet were trained. The accuracy results of these DL models were then compared. The reasons for choosing these five different DL models & metrics, the process of creating the dataset, and the experiments were explained in the corresponding sections of this study.

LITERATURE REVIEW

The presence of various technologies in the tourism business is become more evident. In our literature review, we examined articles that used similar methodologies, as well as studies that focused on the intersection of tourism and technology. These reviews included comparisons, findings and discussions that highlighted gaps and needs within the tourism industry in terms of technological advances.

The content, information and media data (images – videos of a hotel/holiday home) directly affects the decision of potential tourists for a destination (hotel, holiday home, etc.). Therefore, the provided data need to be correct. There are various studies published in the literature for improving the decision-making process of potential tourists with using technological tools. Kim and Kang (2022) identified the visual elements of tourist attractions with DL. Bozyiğit et al. (2021) provided a hotel image classifier for travel agencies in order to improve the selection process of guests. Yuan et al. (2019) reviewed the technological trends in tourism industry between 1990-2016 and presented that the use of AI, big data and Internet-of-Things (IoT) increased in the recent years. Xiao et al. (2020) performed a visual content mining on the images of tourism destinations and according to the results, it provides an important reference for tourism marketing. Chang et al. (2020) proposed a clean-coast detector using a Convolutional Neural Networks (CNN) image classification for improving the coastal tourism. Pliakos and Kontropoulos (2015) conducted a tourism recommender system based on probabilistic latent semantic analysis (PLSA) for improving the various tourism destinations. Kang et al. (2021) provided a method to explore the tourism activities from social media texts and images for analyzing the emotions of a tourism destination. Law et al. (2019) provided a study on tourism demand forecasting with a DL approach. Marigliano (2024) analyzed and predicted sentiments expressed in tourism reviews using DL. Xu et al. (2024) employed SqueezeNet DL model with Slender West Lake tourism image dataset for providing more scientific reference for the study of tourism images.

We performed a second literature review in the methodological aspect of this study. Rasheed (2019) obtained an average value of 0.84 mAP by using Faster R-CNN and R-CNN networks to classify 20 different dog breeds. Raşo (2019) worked on the stock market forecast using machine learning methods and Investing.com's data between 01.01.2016 and 31.12.2018. Lévy and Jain (2016) conducted DL studies on breast cancer diagnosis using the Digital Database for Screening Mammography (DDSM) dataset. Yeong-gyu and Eui-Young (2016) ensured the classification of characters in the Korean alphabet with the dataset called PHD08. Singla et al. (2016) worked on a separation of the meals like “meal / not meal” using binary classification. Zhou et al. (2017) have developed a DL model that distinguishes whether drivers wear seat belts or not. With a set of 379 MRI data, Wang et al. (2019) worked on a DL model that tests whether a person is drunk or not. Almisreb et al. (2018) focused on the classification of people from ear visuals by applying modifications to the AlexNet model. Toprak (2018) has worked on the identification of individuals crossing railways using the Railway Pedestrian Dataset (RAWPED) in combination with learning DL models. Mehr (2017) worked with Kaggle and Data Science Bowl datasets on lung cancer diagnosis using AlexNet and GoogleNet models. Kılınç (2018) achieved a success rate of 85-90% by using the AlexNet DL model to identify individuals with Down syndrome. Ezel (2018) developed a DL model that translates Turkish Sign Language into written language using AlexNet. Örs (2018) conducted studies on the AlexNet DL model for the classification of wheat types. Kadiroğlu (2019) used AlexNet and VGG-16 DL models for breast cancer detection. Akilotu (2019) conducted classification studies on AlexNet and VGG-16 DL models by using various signals (EEG, Oxygen / Carbon Dioxide) for the detection of obstructive sleep apnea. Seyfioğlu (2017) used GoogleNet, ResNet, and VGGNet models to classify Radio Frequency (RF) waves. Gürkaynak (2018) has worked on ship types classification with ResNet, AlexNet, and VGGNet DL models. Yaman (2018) predicted gender and age from ear images using FERET, UND-F, and UND-J2 datasets along with ResNet and VGG-16 DL models. Abhisheka et al. (2023) performed a comprehensive review of breast cancer detection and classification using DL. Alshmrani et al. (2023) developed a DL architecture in order to classify lung diseases using chest X-ray images. Gupta and Bajaj (2023) proposed a DL framework to classify the screening of COVID-19 from CT scans. Algani et al. (2023) used Ant Colony Optimization with CNN to identify the leaf diseases. Tahir et al. (2023) proposed a DL based skin cancer classification network, which they named CSCC_Net, and performed the tests on ISIC 2020, HAM10000, and DermIS datasets. Mira et al. (2024) developed a system for early diagnosis of oral cancer with using DL and data augmentation. Gupta et al. (2024) reviewed the studies on the prediction of the potato disease using IoT, Machine Learning and Image Classification.

MATERIAL AND METHODS

A wide variety of technological concepts are used in the management of tourism and holiday processes. Under this headline, we provided the materials and methods in this study as well as the relation between tourism and DL.

Deep Learning, in its most general form, is a machine learning field used in solving problems and performing actions such as analysis, inference, observation, and learning by using large amounts of data. Unlike traditional machine learning algorithms, DL models can be in different hierarchical structures (Kayaalp & Süzen, 2018). DL is the methods and models that learn the representations at different levels on data with complex relationships and it is a sub-field of machine learning. DL methods developed in recent years are influenced by signal and information processing techniques (Deng & Yu, 2013). DL is the subfield of Artificial Neural Networks (ANN). It is the type of ANN that works to get a certain output value from pure data with nonlinear transformations. It is used in many applications such as natural language processing, image recognition and classification, real-time translation, etc. (Future of Privacy Forum, 2018).

In the literature review, several cases of use of DL in the tourism context were identified, such as demand forecasting, review sentiment analysis, price and availability regression, and user experience. DL and AI have the potential to benefit both guests and key stakeholders, including tourism agencies, hotels, booking platforms and other related parties. For guests, DL can provide accurate information and a significantly improved user experience. For other stakeholders, DL offers improved forecasting capabilities, better insight into availability and pricing trends, and valuable feedback from guest reviews. These technological tools and improvements ultimately lead to a better experience and outlook for everyone involved in the tourism industry.

CNNs are a type of multi-layer perceptron network (Multi Layer Perceptron - MLP). CNN is a DL architecture used for image analysis, classification, recognition, and segmentation. It is an architecture that works with the mathematical convolution (Şeker et al., 2017). It extracts information by passing the image, which has been taken from the input layer through different processes in other layers. An example of a convolution use case in CNN can be the removal or detection of the edges in the image data. It is possible to perform different operations by using pooling, dropout, etc. layers (Raşo, 2019). An example CNN model is given in Figure 1.

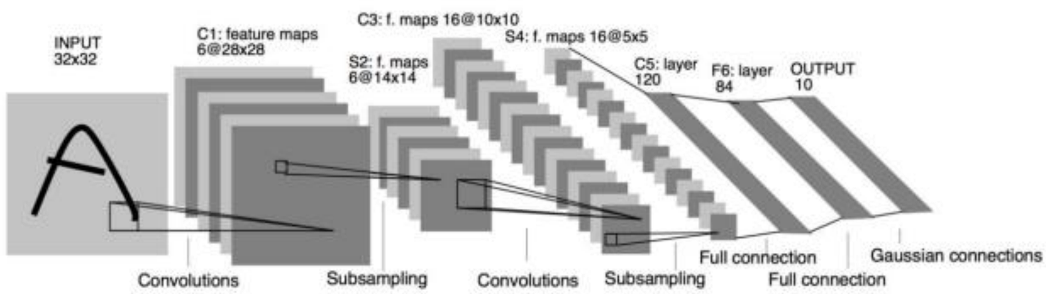

Figure 1. *An example CNN model*

Nowadays, DL networks with different layer combinations or different complexity rates are widely used in literature. The hardware and software that the DL network runs on have a direct effect on performance and efficiency (Shi et al., 2017). We used an appropriate computer in terms of up-to-datedness and cost for our DL training. We preferred TensorFlow and Keras (2019) libraries, because they are easy to use. The DL computer that we used for this study is summarized in Table 4.

Table 4. *Hardware specifications used in the study*

Specification	Explanation
GPU	NVidia GTX 2080 Ti
CPU	AMD Ryzen ThreadRipper 2950X
RAM	64 GB
Operating System	Ubuntu Linux

In recent years, the number and awareness of successful DL models in the literature has increased with competitions. ImageNet Large Scale Visual Recognition Challenge (ILSVRC) competition, which has been held regularly every year since 2010, has become a standard benchmark in the field of object classification. Along with this competition, PASCAL Visual Object Classes (VOC) have an important place as well (Russakovsky et al., 2015). We chose to use the DL models ResNet, DenseNet, VGGNet, Inception v3, and NASNet for the following reasons;

- Widespread preference in literature: These DL models are widely preferred in the literature and have demonstrated reliable accuracy and loss results across various datasets.
- Objective dataset comparison: By introducing a new dataset in this study, we aimed to compare the accuracy and loss of these well-established DL models to evaluate our dataset as objectively as possible.
- Relevance to tourism studies: These DL models have been used in several tourism-related studies identified in our literature review, providing us with a solid basis for effectively examining and comparing our results effectively.

ResNet is a very deep network structure that can reach up to 152 layers and has configurations in different layer numbers. It won first place in the ILSVRC 2015 classification competition. In the training and backward propagation processes in DL network structures, there may be situations of vanishing and/or explosion. This is a problem caused by a very deep layer structure rather than an overfitting problem. The value obtained as a result of multiplying very small numbers may be zero, in this case, there is a vanishing. As a result of multiplying very large numbers, the value obtained may be extremely high, in this case, there is an explosion situation. The expectation is to get better training and testing processes in DL network structures. However, the examples and research from previous articles show different results. ResNet provides a solution to this problem with shortcut connections. The *x* value obtained at one point in the model is added to the output value after several weight layers using these shortcut connections. In this way, even after a vanishing/explosion problem between weight layers, the *x* value from a few steps ago is preserved. It is observed that with this solution, the network can be optimized more easily, the complexity does not increase, and the accuracy result is better. In this study, the 50-layer structure of the ResNet model is preferred. A visual representation of the shortcut transfer process is presented in Figure 2 (He et al., 2016). ResNet is used for classifying tourism attractions and images in the tourism context, such as the study from Firdaus et al. (2018). ResNet is popular for image classification problems including the tourism context.

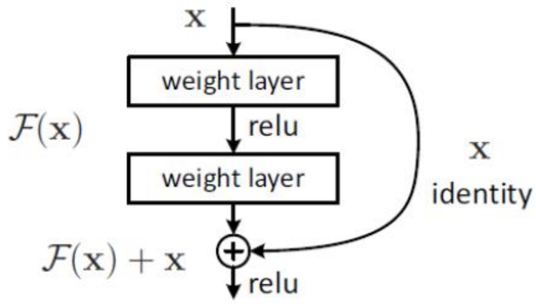

Figure 2. *The shortcut connections in ResNet*

The studies in Convolutional Neural Networks showed that direct shortcut connections made by layers close to the input to the layers close to the output offer better accuracy, efficient training, and deeper network structures. DenseNet, developed based on this observation, connects the output from each layer to other layers located in the forward direction. In classic network structures, *L* layers have *L* connections. But in DenseNet networks, *L* layers have *L(L+1)/2* connections. These forward connections, called Concatenation, allow feature maps to be transferred to other layers. Thus, each further layer receives common data from all previous layers. This allows the network to be thinner and more compact. In addition, it allows to use of a small number of channels and achieves efficiency in aspects of calculation and memory consumption. There are 121, 169, 201, and 264 layered versions of the DenseNet model. Figure 3 shows the connection structure in the DenseNet model (Huang et al., 2018). DenseNet is a different popular DL model for image classification studies, including the destination images creation & classification on social media for the tourism context (Zhao & Agyeiwaah, 2024).

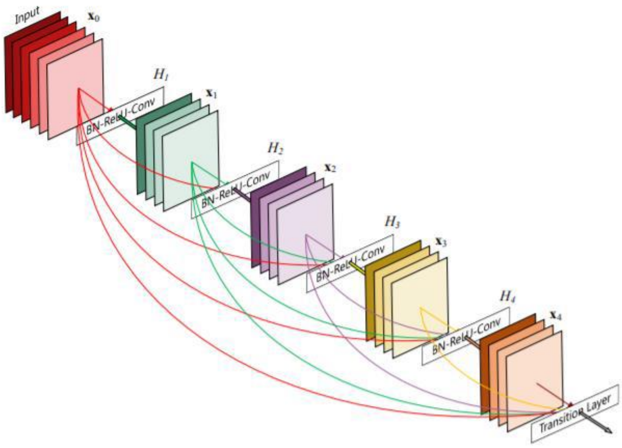

Figure 3. *DenseNet connection structure*

VGGNet is a model that achieved the runner-up first place in the ILSVRC classification task in 2014. In the VGGNet model, the importance of using small-size convolution filters and the depth of the network are shown. Unlike AlexNet and ZFNet models, which succeeded in 2012 and 2013 ILSVRC, VGGNet does not use 11 x 11 or 7 x 7 convolution filters. Instead, it uses 3 x 3 convolution filters with 1 step stride. Because a 3 x 3 convolution filter consisting of 3 layers can cover the same area as a convolution filter with dimensions of 7 x 7. This situation gives some positive benefits. There are 5 different configurations of the VGGNet model with different layer numbers. These are named A, B, C, D, and E (Simonyan & Zisserman, 2014). We preferred VGG-19 (E configuration – in Figure 4) in this DL study, because it is the biggest version of VGGNet. Besides that, VGGNet is preferred in several different tourism studies to classify rural areas, tourist attraction pictures and smart tourism tools (Xie, 2022; Yu, 2024).

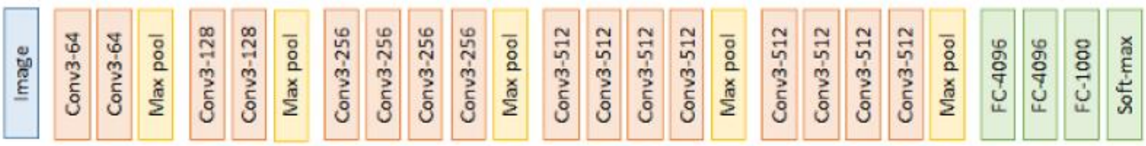

Figure 4. *VGGNet 19 (E) configuration*

The Inception architecture, also used in the Inception v3 model, came with GoogleNet. The GoogleNet model proposed by Szegedy et al. (2015) increases the depth and width while trying to keep the calculation cost at the same rate. For this reason, in this model, the outputs from different convolutional filters merge. The first GoogleNet model is also called Inception v1. Different convolutional filters are used in parallel with inception. The outputs from these filters combine and push to the next steps. A 1x1 convolution matrix is also used in some steps to facilitate complexity and calculation. In addition to 1x1 filter sizes, it is possible to see 3x3, 5x5, and 7x7 filter sizes (Szegedy et al., 2015). The Inception v3 model targets the factorization of the convolution filters. It proposes to use 3 x 3 filters to avoid the cost and computational complexity of 5x5 and 7x7 filters. Instead of one 5 x 5 filter, it is possible to use three 3 x 3 filters. It is the same for 7 x 7 filters. Instead of one 7 x 7 filter, two 3 x 3 filters can be usable. It is possible to get a 28% gain from this factorization. Another thing proposed by Inception v3 is asymmetric convolution factorization. Instead of one 3 x 3 filter, it proposes to use two different convolution filters, the first 3 x 1 and the second 1 x 3. The number of parameters from the 3 x 3 convolution filter is 18. However, the number of parameters from 3 x 1 and 1 x 3 filters is 6. There is a gain of 33% in this factorization step. On the Inception v3, various updates and changes have been made in the Auxiliary classifier, grid system, and Inception modules. Accordingly, the Inception v3 model has maintained the same efficiency level with less cost (Szegedy et al., 2016). An example of the Inception module and an example of the performed filter factorization are given in Figure 5. Inception v3 is preferred in different studies for image classification and feature extraction. There are various studies in tourism field employed Inception v3 for classifying tourists' photos and exploring tourism destinations' images (Bozyiğit, 2021; Kim et al., 2021).

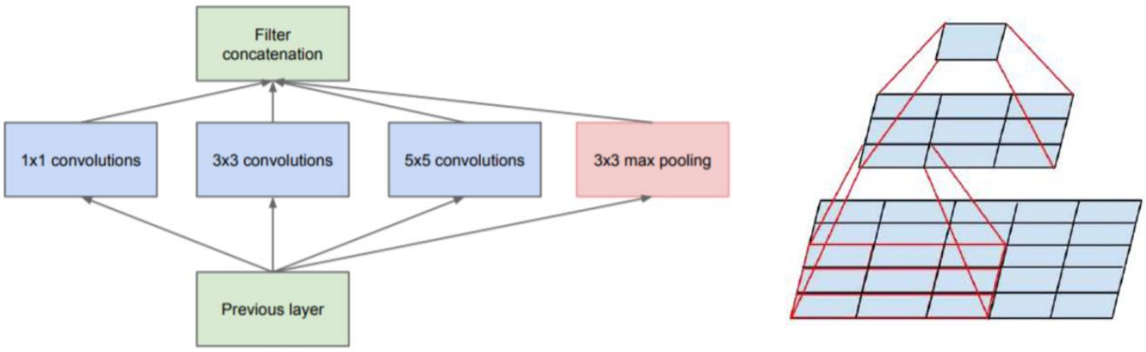

Figure 5. *Inception module (left) and a sample factorization (right)*

NASNet is a model developed by the Google Brain team for the CIFAR-10 dataset. With less complexity and a small model size, NASNet can give good results. The NASNet model does not consist of fixed-definition blocks or cells. Unlike supervised and unsupervised learning methods, it uses reinforcement learning methods. In the NASNet model, there are two different cell types: Normal Cell and Reduction Cell. Convolution operations are performed in normal and reduction cells.

However, the only difference is that the outputs from the reduction cells have a reduced size. With Recurrent Neural Network (RNN), the normal and reduction cells are searched in a search space. h_i and h_{i-1} states are transferred to each selected cell. These states are transferred from the previous layer or the input data. Considering these two states, RNN makes the prediction operations (Zoph et al., 2018). We decided to use the NASNet Mobile version for this study, because it is a lighter version than NASNet. NASNet is employed by different tourism studies for example landmark recognition models (Razali et al., 2023).

The dataset is a key parameter for the ML and DL projects. The quality of the dataset directly affects the success and error rates. The dataset was created specific for this study. The source of the data is a tourism reservations company based in Germany. An official permission from the tourism company was obtained by the researchers for processing their images and creating a dataset. More than 300,000 room images were taken from the company and cleared and labeled each of them individually. Labeling and clearing process have been achieved manually and took approximately 2 months to be completed. At the end of labelling and clearing process, 70,000 images were determined which can be used for training. 5 different labels were used; “kitchen, bathroom, bedroom, living room and garden”. For test and validation of the data, the public room images from various visual media sources such as Flickr were collected. Flickr API Key was obtained in order to fetch images from Flickr. The descriptive statistics of the dataset are summarized in Table 5.

Table 5. *Descriptive statistics of the dataset*

Label	Training Data	Test Data	Validation Data
Kitchen	14,000	1,000	1,000
Bathroom	14,000	1,000	1,000
Bedroom	14,000	1,000	1,000
Living Room	14,000	1,000	1,000
Garden	14,000	1,000	1,000
Sum	**70,000**	**5,000**	**5,000**
General Sum	**80,000 (Including Test & Validation Data)**		

The images in the dataset mainly contain German holiday homes. In addition, there are holiday home images of other different locations, especially the USA (United States of America), Spain, and France. Most of the images in Germany are holiday homes on the Baltic Sea coast in the northern region. Images in the dataset have different labels as well as different qualities. For example, the dataset contains different numbers of images of untidy, tidy, or dirty rooms. Researchers tried to represent as much as possible different qualities of data in the dataset. Sample images from the dataset are given in Figure 6.

Figure 6. *Sample images in the dataset*

A User Interface (UI) was developed to test the predictions of the DL models. The users can be able to easily see the results of the model predictions with this UI by selecting the images they want to test. It is given in Figure 7.

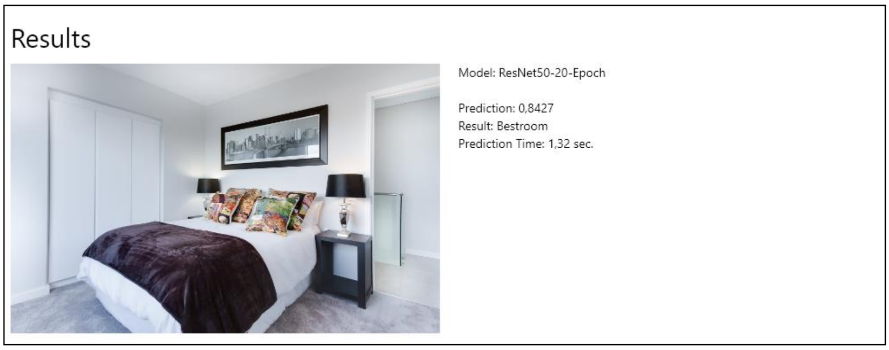

Figure 7. *UI preview for the prediction process*

APPLICATION

Information technologies are frequently used to solve various problems or achieve improvements in the tourism business. In this section, the application stages of the study are explained.

Nowadays in DL applications, the state of the dataset is a factor that directly affects the success of the study (Zhu et al., 2015). The dataset, which is described in the previous section of the study, belongs to a tourism reservations company based in Germany. This dataset was created by extracting the data in the company database. Various problems have been encountered in the extraction process. The first problem (Problem 1) is that the images are dynamically tagged. It is not known exactly which label belongs to the image or not because users can tag the images with a free text area as they wish. For example, a kitchen image can be tagged with "General view of the kitchen", "Dining table in the kitchen", "Microwave oven" or various descriptions and wordings. The users can decide whether to use the word "Kitchen" or not in the tag definitions of the image. If the users wish, they may not use the word "Kitchen" at all, even leave this label field blank or name it in any language. Another problem (Problem 2) from the tagging is the differences in perspective. The homeowners can capture a photo of the garden from the kitchen window and name these kinds of photos in different ways. As an example, a photo of a balcony may contain labels such as "Overview from the kitchen", "View from the kitchen" or the word "kitchen" but not directly related to the kitchen. In this case, filtering the images by the word "Kitchen" can give different unexpected images and this causes data pollution. Another problem arises while extracting the images from single-room houses/apartments (Problem 3). A photo frame can contain items depicting the kitchen, living room, or different kinds of rooms. It is not possible to categorize these kinds of photos correctly. A different problem (Problem 4) was found during the extraction of the images for the garden category. Homeowners (users) can tag the images with "General view of the house", "Front garden", "Garden view" and so on. In these cases, the garden picture often contains a house, apartment, or concrete building in the captured image. Many garden images could not be added to the dataset due to this problem. The visual representations of the explained problems are presented in Figure 8.

Figure 8. *The visual representations of the problems (Left to right number 1,2,3,4)*

Approximately 300,000 images were extracted from the company database. Researchers faced the problems that are described above. The study continued with 70,000 images after the cleaning and labeling process and these images were used in the training set. All these selected images are only used for training. Test and validation sets created from various visual media sources like Flickr (from Flickr API).

As stated in the previous sections, this study used ResNet, DenseNet, VGGNet, Inception v3, and NASNet Mobile models with Keras and TensorFlow libraries. The ResNet model used in this study has a 50-layer structure and the DenseNet model has a 201-layer structure. Both models including VGGNet 19, Inception v3, and NASNet Mobile used together with the Adam optimizer, ReLU activation function, and Categorical Cross Entropy error function. The reasons for this decision are the training time and size limits. All models were trained as 10 and 20 epochs with a batch size of 8. The way of using the dataset in the training process is given in Figure 9 and the pseudo-code of this process in Figure 10.

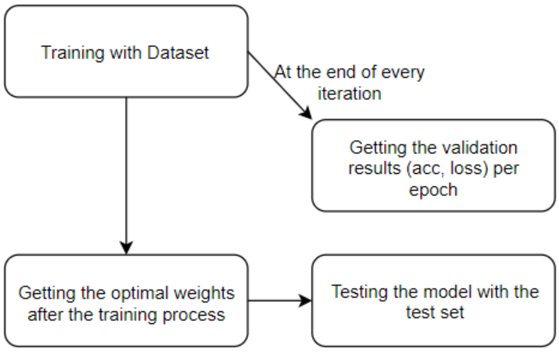

Figure 9. *Usages of the training, test, and validation sets*

```
import Keras
import TensorFlow // Including Keras, TensorFlow and other modules

train_data_generator = ImageDataGenerator(...) // flow_from_directory
validation_data_generator = ImageDataGenerator(...) //flow_from_directory

model = Model // Implementation of the model with layer blocks
model.compile(...)
model.fit_generator(...)
model.save(...)
```

Figure 10. *Pseudo code of the training*

ASSESSMENT

This section presents the findings of the training, testing, and validation processes of the DL models with the described dataset. Researchers determined the epoch number by the test on the ResNet 50 model. ResNet 50 model has been trained in 10, 20, and 50 epochs. The decision was made to do only 10 and 20 epochs of training according to the accuracy, error, and training time results. The reason for this decision is that there is a difference of 27,135 seconds between 20 and 50 epoch training, despite this difference, a 1.38% better accuracy rate has been achieved. The outputs of the training processes are given in Table 6. Assessment was based on the accuracy and loss outputs of the models. The literature showed that accuracy and loss metrics are widely used for evaluation in similar studies. Therefore, these metrics were chosen to provide a clear, objective measure of model performance. The hyperparameter details of the models are presented in Table 7.

Table 6. *Comparison of 10, 20, and 50 epoch training results of the ResNet 50*

Epoch	**Training Time (Second)**	**Accuracy (%)**	**Loss (%)**
10	9,428	96.04	11.60
20	18,740	97.40	7.51
50	45,875	98.78	3.67

Table 7. *Hyperparameter details of the DL models (FC: Fully-Connected)*

Model	**Hyperparameter Details**
ResNet50	Input shape & Tensor: None
	Pooling: None
	FC-Layer: Yes
	Classifier Activation: Softmax
DenseNet201	Input shape & Tensor: None
	Pooling: None
	FC-Layer: Yes
	Classifier Activation: Softmax
VGGNet19	Input shape & Tensor: None
	Pooling: None
	FC-Layer: Yes
	Classifier Activation: Softmax
Inception v3	Input shape & Tensor: None
	Pooling: None
	FC-Layer: Yes
	Classifier Activation: Softmax
NASNet (M)	Input shape & Tensor: None
	Pooling: None
	FC-Layer: Yes
	Classifier Activation: Softmax

As a first step, the ResNet 50 model was trained for 20 epochs. This 20-epoch training lasted 18,740 seconds. On average, 937 seconds are required per epoch. At the end of the training process, an accuracy rate of 97.40% was achieved and a loss rate of 7.51%. Later, another training process was performed with 10 epochs on ResNet 50 using the same dataset, parameters, and conditions. This training process was completed in a total of 9,428 seconds. On average, 942.8 seconds are required per epoch. An accuracy rate of 96.04% was observed and a loss rate of 11.60% at the end of the training process. The accuracy–loss graphics of the 20 and 10 epoch training processes are summarized in Figure 11.

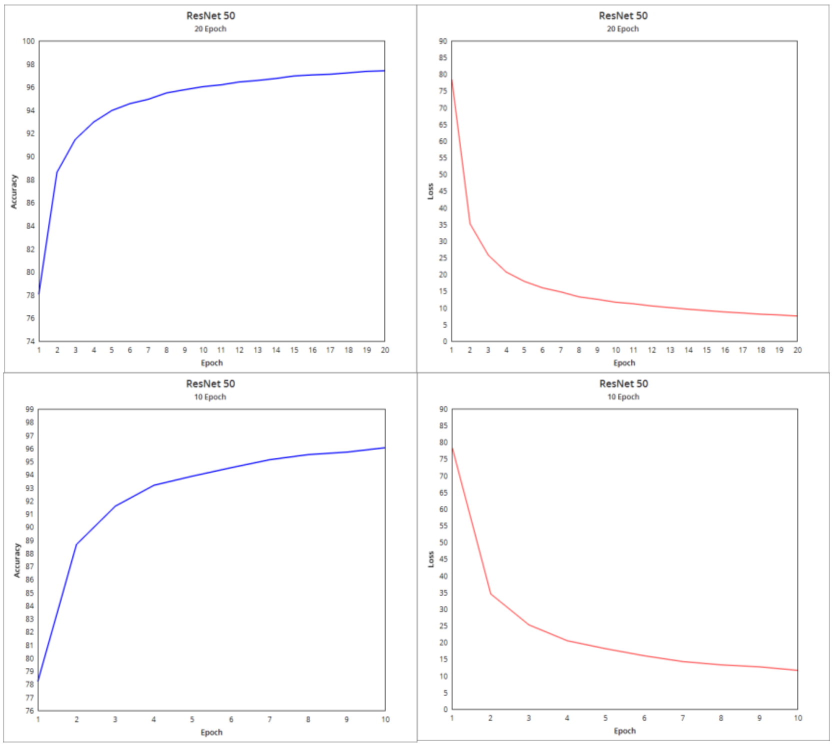

Figure 11. *ResNet 50 accuracy – loss graphics (20 epochs: above, 10 epochs: below, blue: accuracy, red: loss)*

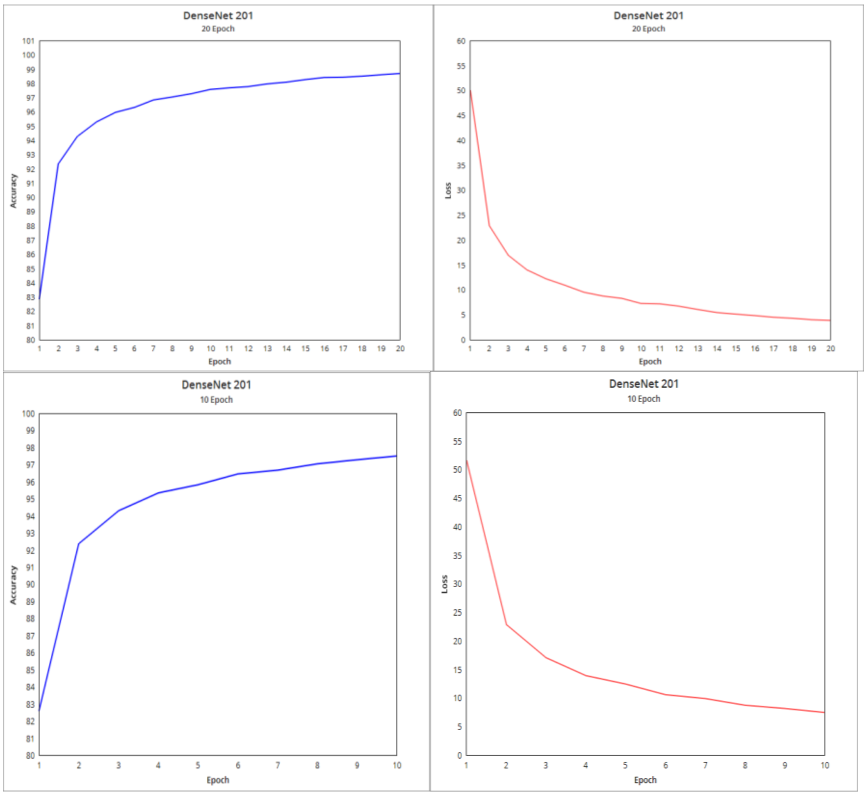

Figure 12. *DenseNet 201 accuracy – loss graphics (20 epochs: above, 10 epochs: below, blue: accuracy, red: loss)*

Moreover, the DenseNet 201 model was trained with 20 epochs using the described dataset and parameters in previous sections. The training took 30,060 seconds with a 98.69% accuracy rate and a 3.87% loss rate. On average, 1,503 seconds are required per epoch. In the second step, the DenseNet 201 model was trained for 10 epochs with the same parameters and conditions. The training has been completed in a total of 15,055 seconds. On average, 1,505.5 seconds are required per epoch. The accuracy-loss graphics of the DenseNet 201 model are summarized in Figure 12.

Following a similar approach, the VGGNet 19 version (E) was trained with 20 epochs as a first step. The training time finished in 16,782 seconds and the average training time per epoch was 839.1 seconds. A 97.31% accuracy rate and a 7.79% loss rate were achieved for 20 epochs of training. As a second step, 10 epochs training was performed on VGGNet 19. The 10-epoch training process was completed in a total of 8,409 seconds. On average, 840.9 seconds are required per epoch. The accuracy–loss graphics of the VGGNet 19 model are summarized in Figure 13.

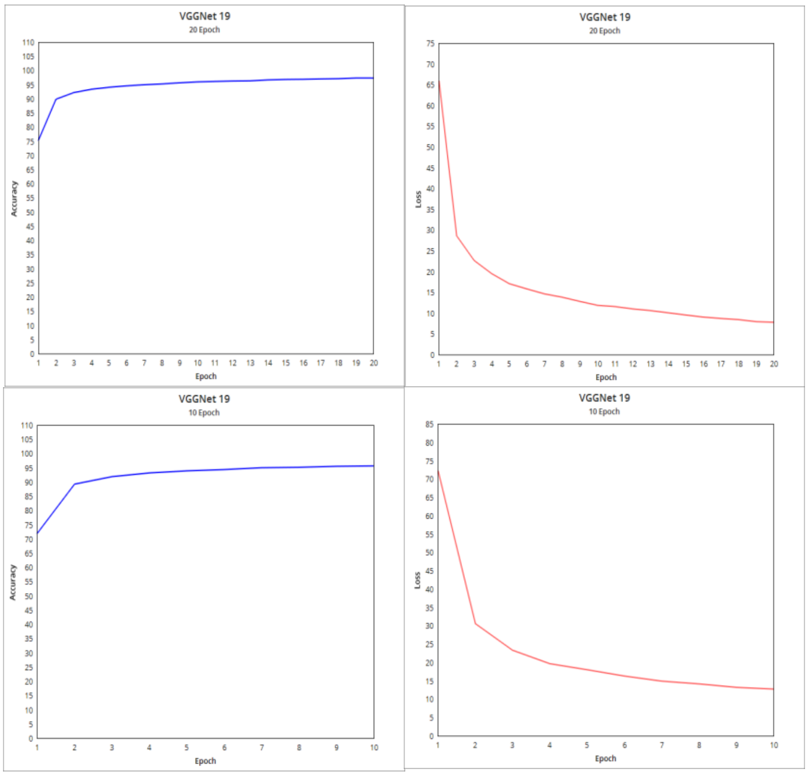

Figure 13. *VGGNet 19 accuracy – loss graphics (20 epochs: above, 10 epochs: below, blue: accuracy, red: loss)*

Later, the Inception v3 model with 20 epochs was trained as a first step. This training took 20,202 seconds in total. Training per epoch was 1,010.1 seconds (average). At the end of these 20 epochs of training, a 97.33%

accuracy rate was achieved with a 7.61% loss rate. The second step of Inception v3 training with 10 epochs was completed in 10,002 seconds. On average 1,000.2 seconds are required per epoch. We ended up with a 95.71% accuracy rate and a 12.38% loss rate for 10 epochs of training. The statistics of Inception v3 training are summarized in Figure 14.

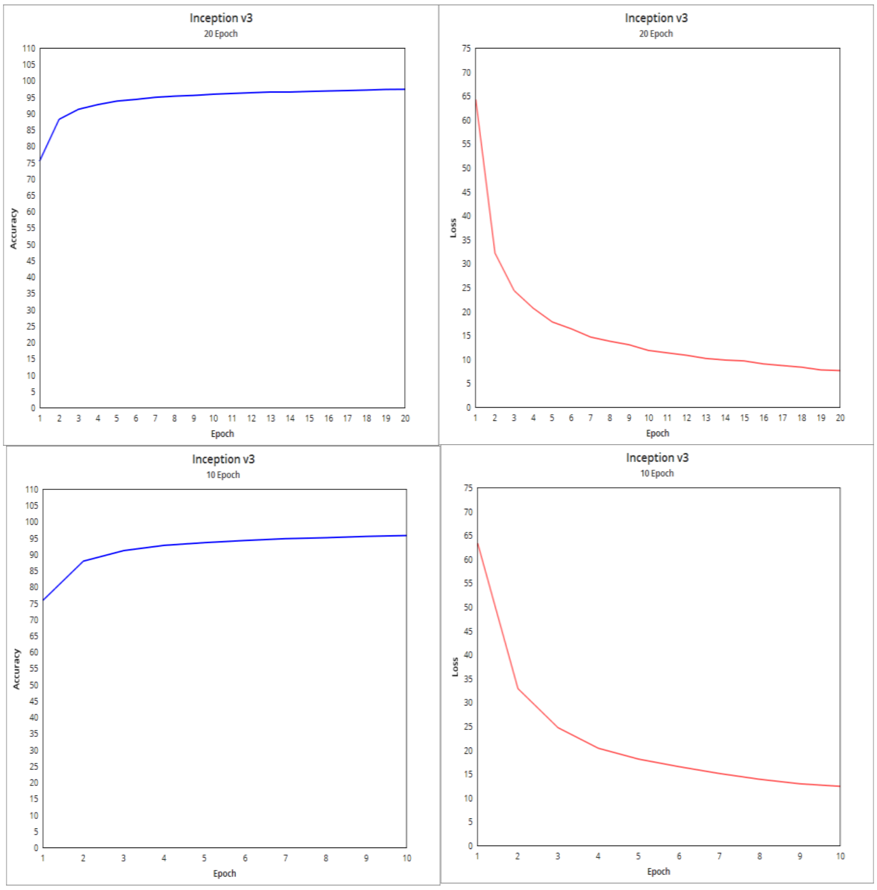

Figure 14. *Inception v3 accuracy – loss graphics (20 epochs: above, 10 epochs: below, blue: accuracy, red: loss)*

The NASNet Mobile model was trained for 20 epochs. This 20-epoch training lasted 34,241 seconds. On average, 1,712.05 seconds are required per epoch. At the end of 20 epoch training processes, an accuracy rate of 97.01% and a loss rate of 8.51% were obtained. 10 epochs of training on the NASNet Mobile model was also performed with the same parameters and conditions. This training has been performed in a total of 17,103 seconds. On average, 1,710.3 seconds are required per epoch. An accuracy rate of 95.41% was achieved with a loss rate of 12.98%. The accuracy–loss graphics of the 20 and 10 epoch training processes are summarized in Figure 15.

Lastly, a balanced dataset was created for the training and testing of the DL models. The aim was to see the quality of the dataset and perform a second test. 20 images from the test set were selected, and a prediction was performed using the DL models we trained with 20 epochs. As a result, sufficient prediction results were obtained from all DL models. However, some DL models performed much better than the rest of the models. According to this testing, the Inception v3 model is slightly less successful than other models. The prediction outputs of these 20 images on the DL models are summarized in Table 8 (Balga, 2020).

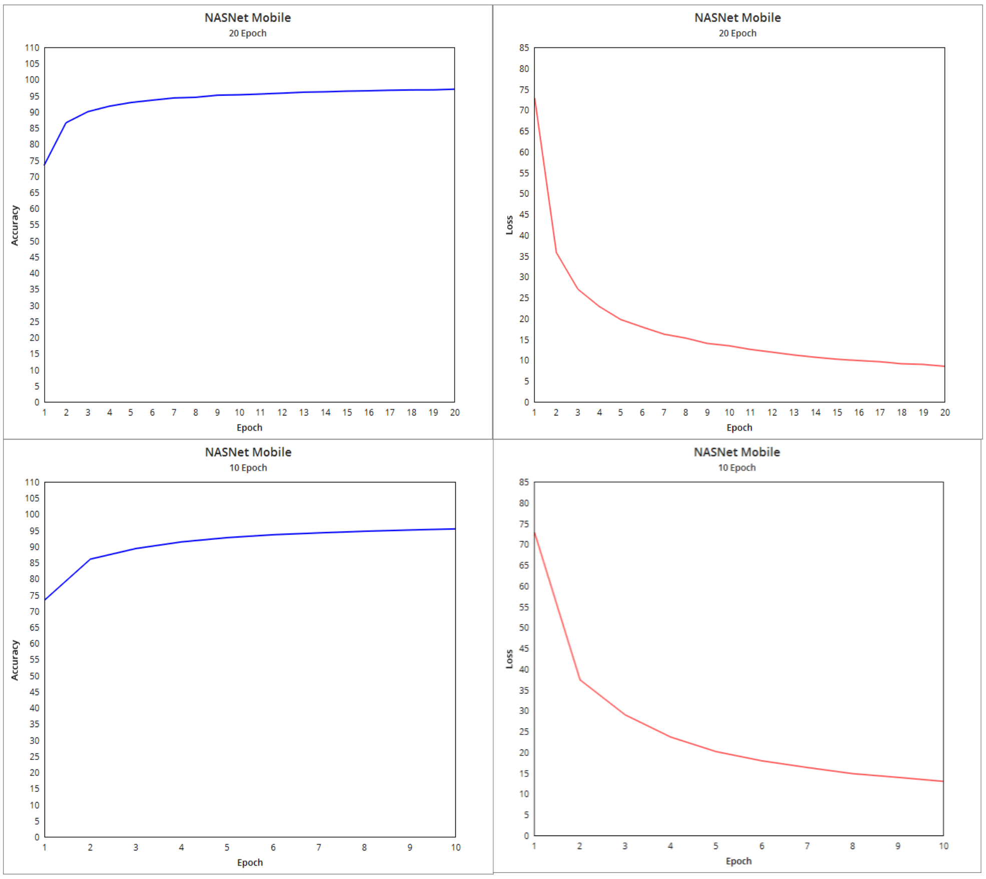

Figure 15. *NASNet Mobile accuracy – loss graphics (20 epochs: above, 10 epochs: below, blue: accuracy, red: loss)*

Table 8. *Predictions from the models (correct prediction / total image) ResNet and VGGNet performed better than other DL models*

Label	**ResNet**	**DenseNet**	**VGGNet**	**Inception v3**	**NASNet**
Bathroom	20/20	19/20	20/20	16/20	18/20
Living Room	19/20	20/20	19/20	17/20	19/20
Bedroom	19/20	14/20	19/20	13/20	19/20
Kitchen	20/20	20/20	20/20	14/20	20/20
Garden	20/20	20/20	20/20	20/20	18/20
Total	98/100	93/100	98/100	80/100	94/100

RESULTS

Many different types of tourism can be seen in the world. In general, tourism directly helps the economy of the region and/or the country. Density and activity in tourism regions increase or decrease depending on national and international holidays and seasonal differences (Martin et al., 2018). There are different types of accommodation possibilities in tourist regions such as hotels, holiday homes, etc. This study focused on the holiday homes. Holiday homes are areas of rented accommodation, usually short-term, located in a house or apartment, with a specific area and facility. It is possible to see different holiday houses depending on location, possibility, and budget (Scanlon et al., 2014).

There are sociological, economic, philosophical, and technological changes that have an impact on the tourism area and the behavior of consumers. There are different ways to book and access the accommodation possibilities and pricing options such as hotel/vacation home websites, reservation portals, agencies, and other internet platforms. Currently, about 25% of bookings in the world are made via the Internet (Crnojevac et al., 2010; Oskam & Boswijk, 2016). In addition, it is seen that various artificial intelligence applications, decision-support structures, chat assistants, and other technological applications take place in the tourism business. Online booking portals replaced face-to-face reservations in the past. In these online booking portals, there are a wide variety of applications and marketing strategies such as offering the best price and options to the customer, helping the decision process, personal offers, and price and location recommendations. Behind these applications, there are various technologies such as algorithms, big data, artificial intelligence, mobile applications, chat assistants, etc. (Zsarnoczky, 2017). Basically, this study identified different use-cases of DL and other technological improvements in the tourism context. These use-cases can improve the user experience and offer a better insights and forecasting.

The main objective of this study is to explore the application of DL models for classifying the holiday homes' images. Therefore, a unique dataset was created from a German-based tourism company for holiday homes' room classification, training models, and comparison based on the results with accuracy assessment. As a result, the study aimed to improve and optimize the user experience, data correctness, higher forecasting, and better overview options. Keras and TensorFlow libraries were used for the execution and development of the models.

As a first step, the data of the German-based tourism company was obtained. A dataset was created for this study. The problems and difficulties of creating your dataset by cleaning and labeling the data were explained. 70,000 room images were extracted and labeled from the tourism company. An additional 10,000 images were used for the test and validation set. The images for the test and validation set were collected from public sources like Flickr (using Flickr API) and other sources and APIs. At the end, we had 80,000 room images in the dataset.

As a second step, the decisions, comparisons, advantages, and problems of the DL models were explained. ResNet, DenseNet, VGGNet, Inception v3, and NASNet models were used. These models are frequently used in the literature as well as competitions like ILSVRC. The models were trained with 10 and 20 epochs on a high-end computer with Nvidia GTX 2080 Ti GPU. These models were implemented using Keras and TensorFlow.

Table 9. *Summary of the DL models' accuracy and loss outputs*

Model	**Epoch**	**Accuracy (%)**	**Loss (%)**
ResNet 50	10	96.04	11.60
ResNet 50	20	97.40	7.51
DenseNet 201	10	97.50	7.45
DenseNet 201	20	98.69	3.87
VGGNet 19 (E)	10	95.65	12.74
VGGNet 19 (E)	20	97.31	7.79
Inception v3	10	95.71	12.38
Inception v3	20	97.33	7.61
NASNet Mobile	10	95.41	12.98
NASNet Mobile	20	97.21	8.51

In general, successful accuracy and loss rates were obtained from the DL models. According to our findings, the ResNet, DenseNet, VGGNet, and NASNet models achieved better results than Inception v3. Moreover, researchers performed their prediction test on the 20 epochs trained models by randomly getting 20 room images from the test set and making the predictions on all models. ResNet and VGGNet models performed a 98% success rate on the prediction test. The summary of accuracy and loss rates of the DL models are shown in Table 9. To summarize, the experimental results of the deep learning models on different sets of room images were presented in Figure 16, with the corresponding statistics detailed in Table 10.

Figure 16. *Randomly selected different sets of room images. These images predicted on the five DL models and the results detailed in Table 10. From left to right, up to bottom we numbered the images numerically. The 1st image represents a bathroom and the 10th image represents a garden.*

Table 10. *Randomly selected images' statistical results from the five DL models. The predictions represent the predicted classes and prediction rate. The images shown in Figure 16 in a numerical order.*

Image No.	Label	ResNet Pred.	DenseNet Pred.	VGGNet Pred.	Inception v3 Pred.	NASNET Pred.
1	Bathroom	Bathroom (94.06%)	Kitchen (97.23%)	Bathroom (78.24) %	Kitchen (40.63%)	Kitchen (75.05%)
2	Bathroom	Bathroom (100%)	Bathroom (100%)	Bathroom (100%)	Bathroom (99.45%)	Bathroom (99.98%)
3	Living Room	Living Room (100%)	Living Room (100%)	Living Room (99.50%)	Living Room (45.80%)	Living Room (99.92%)
4	Living Room	Living Room (97.09%)	Living Room (99.51%)	Livin Room (99.88%)	Living Room (70.86%)	Living Room (85.30%)
5	Bedroom	Bedroom (10%)	Bedroom (90.79%)	Bedroom (99.99%)	Bedroom (100%)	Bedroom (99.99%)
6	Bedroom	Bedroom (100%)	Bedroom (100%)	Bedroom (100%)	Bedroom (96.60%)	Bedroom (99.99%)
7	Kitchen	Kitchen (99.96%)	Kitchen (100%)	Kitchen (99.99%)	Kitchen (84.59%)	Kitchen (99.99%)
8	Kitchen	Kitchen (99.99%)	Kitchen (100%)	Kitchen (100%)	Kitchen (80.69%)	Kitchen (99.92%)
9	Garden	Garden (99.98%)	Garden (99.99%)	Garden (100%)	Garden (94.61%)	Living Room (54.65%)
10	Garden	Garden (100%)	Garden (100%)	Garden (99.99%)	Garden (98.28)	Kitchen (51.30%)

Conclusions and Future Work

The main objective of the present study is to explore the room image classification related to holiday homes with DL models, which can support achieving the accuracy and efficiency of automated systems in the tourism industry. Therefore, a unique dataset was created, developed and designed. Five different popular DL models – ResNet, DenseNet, VGGNet, Inception v3 and NASNet Mobile – were trained on the dataset. Accuracy and loss metrics of these DL models were evaluated to determine their sustainability for applications in tourism industry.

Employing AI and technological tools for tourism applications can reduce the manual work and effort of guests, landlords and other partners such as online reservation platforms. Classifying the holiday home room images are a time-consuming task and requires manual work. It can be open to human-errors such as wrong classifications. This study presents new high accuracy holiday home image classification tool based on five different deep learning models and a unique dataset. The study further reduces the effort for holiday homes room images classification, increases the efficiency, and enhances the users' experiences, and boosts reservations in the tourism industry.

In every DL study, the size, quality, and diversity of the dataset are important factors as in this case study. The fact that the dataset is clean, diverse, and contains as much data as possible can give a positive result for the training. Besides that, the accuracy can be boosted by optimizing the hyperparameters or using different tools like Regularization techniques. A unique dataset was created specifically for this case study, which includes 80,000 room images. The training was performed on five different DL models, and a comparison was made by using this unique dataset. As a result, the study shows that the DL model structures have an effect on the accuracy of the task directly. The best accuracy result (98.69%) was observed with DenseNet 201 and 20 epochs training, the worst (95.41%) with NASNet Mobile and 10 epochs training. Having a high accuracy and low loss rate means a stable and successful image classification and this is also beneficial for tourism industry and applications. Results of the current work was compared with other most similar tourism related studies in the literature, in Table 11. According to this comparison, this research achieved similar or slightly better results than other works. Results of the study can be used as a real-world implication in the tourism industry.

Table 11. *Comparison of our results with the other most similar studies in tourism industry*

Study	Results	Our Results		
		Model	Epoch	Accuracy (%)
Bozyiğit et al. (2021)	VGG-16 84% Accuracy	ResNet 50	10	96.04
Chang et al. (2020)	CNN 97.73% Accuracy	ResNet 50	20	97.40
Xu et al. (2024)	SqueezeNet 85.75% Validation Accuracy	DenseNet 201	10	97.50
Marigliano (2024)	80% Accuracy	DenseNet 201	20	98.69
		VGGNet 19 (E)	10	95.65
		VGGNet 19 (E)	20	97.31
		Inception v3	10	95.71
		Inception v3	20	97.33
		NASNet Mobile	10	95.41
		NASNet Mobile	20	97.21

The accuracies can be adjusted with different options like hyperparameter selections, loss & optimizer functions, combinations with different models & algorithms, regularization approaches, and so on. Different models, data augmentation methods, RNN, and GAN based approaches can be studied as future work. It is also possible to combine different datasets, social media images for image classification tasks to boost tourism and destinations marketing. These aspects can be considered as future work. Different practical applications, such as ChatGPT and similar tools can be also combined with the image classification tasks in tourism industry. There are also different DL model frameworks for specific tasks as we have seen in our literature review. This aspect can be also studied as a future work and combined with different models and techniques (Balga, 2020).

REFERENCES

Abhisheka, B., Biswas, S. K., & Purkayastha, B. (2023). A Comprehensive Review on Breast Cancer Detection, Classification and Segmentation Using Deep Learning. *Archives of Computational Methods in Engineering, 30*(8), 5023-5052. https://doi.org/10.1007/s11831-023-09968-z

Alshmrani, G. M. M., Ni, Q., Jiang, R., Pervaiz, H., & Elshennawy, N. M. (2023). A deep learning architecture for multi-class lung diseases classification using chest X-ray (CXR) images. *Alexandria Engineering Journal, 64*, 923-935. https://doi.org/10.1016/j.aej.2022.10.053

Algani, Y. M. A., Caro, O. J. M., Bravo, L. M. R., Kaur, C., Ansari, M. S. A., & Bala, B. K. (2023). Leaf disease identification and classification using optimized deep learning. *Measurement: Sensors, 25*, 100643.

Akılotu, B. N. (2019). Osas hastaları ile sağlıklı bireylerdeki nabız geçiş sürelerinin makina öğrenmesi teknikleriyle sınıflandırılması. Fırat University, Institute of Science, Master Thesis.

Almisreb, A., A., Jamil, N., & Din, N. M. (2018). Utilizing AlexNet Deep Transfer Learning for Ear Recognition. *Fourth International Conference on Information Retrieval and Knowledge Management*, 8-12. https://doi.org/10.1109/INFRKM.2018.8464769

Assa Abloy. (2017). Europe's holiday rentals market. Retrieved November 27, 2020, from https://www.assaabloy.de/Other/Testlab/EMEA%20Marketing/SDL/holiday-rental-2017-

09/WEB_BRO%20SDL%E2%80%89%E2%80%89HOLIDAY%20RENTAL%2009%202017%20ENG%20UK-white-paper.pdf

Balga, M. K. (2020). The classification and application of the rooms in holiday homes by deep learning. Selcuk University, Institute of Science, Master Thesis.

Bozyiğit, F., Taşkın, A., Akar, K., & Kılınç, D. (2021). A Deep Learning-Based Hotel Image Classifier for Online Travel Agencies. *DEUFMD, 23*(67), 257-264. https://doi.org/10.21205/deufmd.2021236722

Chang, M., Xing, Y. Y., Zhang, Q. Y., Han, S., & Kim, M. (2020). A CNN Image Classification Analysis for 'Clean-Coast Detector' as Tourism Service Distribution. *Journal of Distribution Science, 18*(1), 15-26. https://doi.org/10.15722/jds.18.1.202001.15

Crnojevac, I. H., Gugić, J., & Karlovčan, S. (2010). eTourism: A comparison of Online and Offline Bookings and the Importance of Hotel Attributes. *Journal of Information and Organizational Sciences, 34*(1), 41-54.

Deng, L., & Yu, D. (2013). Deep Learning: Methods and Applications. *Foundations and Trends in Signal Processing, 7*(3-4), 197-387. http://dx.doi.org/10.1561/2000000039

Ezel, E. (2018). Derin öğrenme yöntemi kullanılarak görüntü-tabanlı türk işaret dili tanıma. Selcuk University, Institute of Science, Master Thesis.

Firdaus, N. M., Chahyati, D., & Fanany, M. I. (2018). Tourist Attractions Classification using ResNet. *International Conference on Advanced Computer Science and Information Systems (ICACSIS)*, 429-433. https://doi.org/10.1109/ICACSIS.2018.8618235

Future of Privacy Forum. (2018). The Privacy Expert's Guide to Artificial Intelligence and Machine Learning. Future of Privacy Forum. Retrieved November 27, 2020, from https://fpf.org/wp-content/uploads/2018/10/FPF_Artificial-Intelligence_Digital.pdf

Gupta, A., Chug, A., & Singh, A. P. (2024). Potato disease prediction using machine learning, image processing and IoT – a systematic literature survey. *Journal of Crop Improvement, 38*(2), 95-137. https://doi.org/10.1080/15427528.2023.2285827

Gupta, K., & Bajaj, V. (2023). Deep learning models-based CT-scan image classification for automated screening of COVID-19. *Biomed Signal Process Control, 80*, 104268. https://doi.org/10.1016/j.bspc.2022.104268

Gürkaynak, C., D. (2018). Fine-tuning convolutional neural Networks for maritime vessel classification, verification, and recognition. Bahçeşehir University, Institute of Science, Master Thesis.

He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep Residual Learning for Image Recognition. *IEEE Conference on Computer Vision and Pattern Recognition*, 770-778. https://doi.org/10.1109/CVPR.2016.90

Huang, G., Liu, Z., Maaten, L., & Weinberger, K., Q. (2018). Densely Connected Convolutional Networks. arXiv preprint arXiv:1608.06993. https://doi.org/10.48550/arXiv.1608.06993

Kadiroğlu, Z. (2019). Histopatolojik meme kanseri görüntülerinin evrişimsel sinir ağları kullanılarak sınıflandırılması. Fırat University, Institute of Science, Master Thesis.

Kang, Y., Cho, N., Park, S., & Kim, J. (2021). Exploring Tourism Activities of Tourists and Residents through Convolutional Neural Network-based SNS Photo Classification. *Journal of the Korean Geographical Society, 56*(3), 247-264. https://doi.org/10.22776/kgs.2021.56.3.247

Kayaalp, K., & Süzen, A. A. (2018). *Derin Öğrenme ve Türkiye'deki Uygulamaları*. İKSAD Publishing House.

Keras. (2019). Retrieved November 27, 2020, from https://keras.io/

Kılınç, H. (2018). Derin öğrenmeli konvolüsyonel sinir ağları (deep learning convolutional neural network) kullanarak fotoğraftan trizomi 21 (down sendromu) tespiti. Çukurova University, Institute of Science, Master Thesis.

Kim, J., Kang, Y., Cho, N., & Park, S. (2021). Classifying Tourists' Photos and Exploring Tourism Destination Image Using a Deep Learning Model. *Abstr. Int. Cartogr. Assoc., 3, 150.* https://doi.org/10.5194/ica-abs-3-150-2021

Kim, J., & Kang, Y. (2022). Automatic Classification of Photos by Tourist Attractions Using Deep Learning Model and Image Feature Vector Clustering. *International Journal of Geo-Information, 11*(4), 245. https://doi.org/10.3390/ijgi11040245

Law, R., Li, G., Fong, D. K. C., Han, X. (2019). Tourism demand forecasting: A deep learning approach. *Annals of Tourism Research, 75*(C), 410-423. https://doi.org/10.1016/j.annals.2019.01.014

Lévy, D., & Jain, A. (2016). Breast Mass Classification from Mammograms using Deep Convolutional Neural Networks. arXiv preprint arXiv: 1612.00542. https://doi.org/10.48550/arXiv.1612.00542

Marigliano, P. (2024). Analyzing tourism reviews using Deep Learning and AI to predict sentiments. *Quality & Quantity*. https://doi.org/10.1007/s11135-024-01840-x

Martín, J. M. M., Martín, J. A. R., Mejía, K. A. Z., & Fernández, J. A. S. (2018). Effects of Vacation Rental Websites on the Concentration of Tourists —Potential Environmental Impacts. An Application to the Balearic Islands in Spain. *International Journal of Environmental Research and Public Health, 15*(2), 347. https://doi.org/10.3390/ijerph15020347

Mehr, H., D. (2017). Classification of lung CT images using deep convolutional neural network. Gazi University, Institute of Science, Master Thesis.

Mira, E. S., Sapri, A. M. S., Aljehani, R. F., Jambi, B. S., Bashir, T., El-Kenawy, E. M., & Saber, M. (2024). Early Diagnosis of Oral Cancer Using Image Processing and Artificial Intelligence. *Fusion: Practice and Applications (FPA), 14*(1), 293-308. https://doi.org/10.54216/FPA.140122

Oskam, J., & Boswijk, A. (2016). Airbnb: the future of networked hospitality businesses. *Journal of Tourism Futures, 2*(1), 22-42. https://doi.org/10.1108/JTF-11-2015-0048

Örs, D. Z. D. (2018). Farklı dalga boylu görüntülerle buğday sınıflandırılması. Eskişehir Osmangazi University, Institute of Science, Master Thesis.

Pliakos, K., & Kontropoulos, C. (2015). Building an image annotation and tourism recommender system. *International Journal on Artificial Intelligence Tools, 24*(5), 1540021. https://doi.org/10.1142/S0218213015400217

Rasheed, S. M. (2019). Object detection from images using deep learning. Fırat University, Institute of Science, Master Thesis.

Raşo, H. (2019). Deep learning based stock market prediction using technical indicators. Gazi University, Institute of Science, Master Thesis.

Razali, M. N., Tony, E. O. N., Ibrahim, A. A. A., Hanapi, R., & Iswandono, Z. (2023). Landmark Recognition Model for Smart Tourism using Lightweight Deep Learning and Linear Discriminant Analysis. *International Journal of Advanced Computer Science and Applications, 14*(2). https://dx.doi.org/10.14569/IJACSA.2023.0140225

Russakovsky, O., Deng, J., Su, H., Krause, J., Satheesh, S., Ma, S., … & Fei-Fei, L. (2015). ImageNet Large Scale Visual Recognition Challenge. arXiv preprint arXiv:1409.0575v3. https://doi.org/10.48550/arXiv.1409.0575

Scanlon, K., Sagor, E., Whitehead, C. (2014). The economic impact of holiday rentals in the UK. HomeAway Final Report London School of Economics. Retrieved September 15, 2019, from https://www.homeaway.co.uk/files/live/sites/hr/files/shared/partnerships/lse/HomeAwayEconomicImpact-Report_November2014-FinalReport.pdf

Seyfioğlu, M., S. (2017). Radar mikro-doppler imza sınıflandırma problemi için derin sinir ağı başlatma ve eğitim metodolojileri. TOBB University of Echonomics & Technology, Institute of Science, Master Thesis.

Shi, S., Wang, Q., Xu, P., & Chu, X. (2017). Benchmarking State-of-the-Art Deep Learning Software Tools. arXiv preprint arXiv:1608.07249v7. https://doi.org/10.48550/arXiv.1608.07249

Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556. https://doi.org/10.48550/arXiv.1409.1556

Singla, A., Yuan, L., & Ebrahimi, T. (2016). Food/Non-food Image Classification and Food Categorization using Pre-Trained GoogLeNet Model. Proceedings of the 2nd International Workshop on Multimedia Assisted Dietary Management, 3-11. https://doi.org/10.1145/2986035.2986039

Statista, (2019). Vacation Rentals. Retrieved November 27, 2020, from https://www.statista.com/outlook/268/100/vacation-rentals/worldwide

Statista. (2023). Preferred summer holiday accommodation among Europeans as of April 2023. Retrieved January 12, 2024, from https://www.statista.com/statistics/868047/summer-holiday-accommodation-preference-europe/

Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., Erhan, D., Vanhoucke, V., & Rabinovich, A. (2015). Going deeper with convolutions. IEEE Conference on Computer Vision and Pattern Recognition, 1-9. https://doi.org/10.1109/CVPR.2015.7298594

Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J., & Wojna, Z. (2016). Rethinking the Inception Architecture for Computer Vision. IEEE Conference on Computer Vision and Pattern Recognition, 2818-2826. https://doi.org/10.1109/CVPR.2016.308

Şeker, A., Diri, B., Balık, H. H. (2017). Derin Öğrenme Yöntemleri ve Uygulamaları Hakkında Bir İnceleme. *Gazi Journal of Engineering Sciences*, *3*(3), 47-64.

Tahir, M., Naeem, A., Malik, H., Tanveer, J., Naqvi, R. A., & Lee, S. (2023). DSCC_Net: Multi-Classification Deep Learning Models for Diagnosing of Skin Cancer Using Dermoscopic Images. *Cancers*, *15*(7), 2179. https://doi.org/10.3390/cancers15072179

Toprak, T. (2018). Pedestrian detection for railway driver support systems. Dokuz Eylül University, Institute of Science, Master Thesis.

Turkish Statistical Institute, (2024). Turizm İstatistikleri. Retrieved August 01, 2024, from https://data.tuik.gov.tr/Bulten/DownloadIstatistikselTablo?p=R7g/EtmQKn964eY48QXFvkOGN/pQOTAdG7WyMsEoEYJsNbTXshXZecQZCHilnFnj

Wang, S., Xie, S., Chen, X., Guttery, D., S., Tang, C., Sun, J., & Zhang, Y. (2019). Alcoholism Identification Based on an AlexNet Transfer Learning Model. *Frontiers in Psychiatry*, *10*(205), 1-13. https://doi.org/10.3389/fpsyt.2019.00205

Xiao, X., Fang, C., & Lin, H. (2020). Characterizing Tourism Destination Image Using Photos' Visual Content. *International Journal of Geo-Information*, *9*(12), 730. https://doi.org/10.3390/ijgi9120730

Xie, O. (2022). Image Retrieval of Tourism Landscape in Rural Revitalization Based on Wireless Communication Network. *Wireless Communications and Mobile Computing*, 7167611. https://doi.org/10.1155/2022/7167611

Xu, L., Chen, X., & Yang, X. (2024). Tourism image classification based on convolutional neural network SqueezeNet-Taking Slender West Lake as an example. *PloS One*, *19*(1), e0295439. https://doi.org/10.1371/journal.pone.0295439

Yaman, D. (2018). Age and Gender Image Classification from Ear Images. İstanbul Technical University, Institute of Science, Master Thesis.

Yeong-gyu, K., & Eui-Young, C. (2016). Streamlined GoogLeNet Algorithm Based on CNN for Korean Character Recognition. *Journal of the Korea Institute of Information and Communication Engineering*, *20*(9), 1657-1665. http://dx.doi.org/10.6109/jkiice.2016.20.9.1657

Yu, H. (2024). Application of the artificial intelligence system based on graphics and vision in ethnic tourism of subtropical grasslands. *Heliyon*, *10*(11), e31442. https://doi.org/10.1016/j.heliyon.2024.e31442

Yuan, Y., Tseng, Y., Ho, C. (2019). Tourism information technology research trends: 1990-2016. *Tourism Review*, *74*(1), 5-19. http://dx.doi.org/10.1108/TR-08-2017-0128

Zhao, Y., & Agyeiwaah, E. (2024). How Do Tourism Stakeholders Co-Create Destination Images with Photos on Social Media?. *Journal of Travel Research*, https://doi.org/10.1177/00472875241253006

Zhou, B., Chen, D., & Wang, X. (2017). Seat Belt Detection Using Convolutional Neural Network BN-AlexNet. ICIC 2017: Intelligent Computing Theories and Application. *Lecture Notes in Computer Science*, *10361*, 384-395. http://dx.doi.org/10.1007/978-3-319-63309-1_36

Zhu, X., Vondrick, C., Ramanan, D., & Fowlkes, C. C. (2015). Do We Need More Training Data or Better Models for Object Detection?. *International Journal of Computer Vision*, *119*, 76-92. https://doi.org/10.1007/s11263-015-0812-2

Zoph, B., Vasudevan, V., Shlens, J., & Le, Q. V. (2018). Learning Transferable Architectures for Scalable Image Recognition. arXiv preprint arXiv: 1707.07012v4. https://doi.org/10.48550/arXiv.1707.07012

Zsarnoczky, M. (2017). How Does Artificial Intelligence Affect Tourism Industry?. *Vadyba / Journal of Management*, *31*(2), 85-90.