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RESEARCH ARTICLE

CLASSIFICATION OF BATHROOM AND BEDROOMS IN HOLIDAY HOMES USING RESNET

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ABSTRACT

People live in houses with different characteristics due to climate, topography and other factors, or are temporarily accommodated in different types of houses due to holiday. These differences, price, size, hardware, type and so on. many parameters. Nowadays, these houses are temporarily rented because of holiday, they are called holiday homes and can be easily rented through various booking portals. Large booking portals use a variety of artificial intelligence applications to assist customers and landlords. The classification of rooms in holiday homes of different types and configurations can also be considered in these applications. In this study, bathrooms and bedrooms in holiday homes were classified using ResNet deep learning network. In the study, a data set containing a total of 20,000 data unique to a reservation portal operating in Europe was used. For the test and validation, a data set consisting of a total of 10,000 data and totally obtained from Flickr was preferred. As a result of the study, 99.55% accuracy rate was obtained.

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INTRODUCTION

From the past to the present day, people live in various housing units to meet the need for housing. Climate, topography, socio-cultural and socioeconomic life have been an element in the shaping of houses (Bozkurt, 2013). Depending on the location, type, function and other purposes of the settlement in today's houses, kitchen, bedroom, bathroom, living room and so on. There are different types of rooms that serve different purposes. For example, there are various differences between urban and rural settlements, soil, wood, reinforced concrete structures and apartment / detached house types, especially room types (Özgür, 2010). Nowadays, bedroom and bathroom in almost every house are the room types used in this study. According to the Turkish Language Association, a bathroom means a place to bathe. The bedroom is a room for sleeping (Türk Dil Kurumu, 2019). It is possible to analyze the situation more clearly by looking at the countries and types of houses in which individuals lived. When the distribution of house types in the European Union (EU) is examined, 41.9% of the population lives in apartments. In Lithuania, Spain, Estonia, Greece and Switzerland, more than 60% of the population lives in apartments. In Croatia, Slovenia, Romania and Hungary, more than half of the population lives in detached houses.

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In the UK, the Netherlands, Ireland, Belgium and Malta, the majority of the population lives in semi-detached houses. Detailed statistics covering 5 European Union countries are shared in Table I (Euro Stat, 2019). Another accommodation environment where people can live temporarily is holiday houses. These houses can be examined in different categories according to location, equipment, number of rooms, house type and budget. Holiday homes, with goods, water, internet, electricity and so on. services are active, daily, weekly or monthly rented houses (Department of Tourism and Commerce Marketing Dubai, 2017). In a statistic published by Statista, holiday preferences of citizens of the European Union were discussed. In the data prepared for 2019, hotels became the first holiday choice with 48%. In second place, holiday houses took the place with 34%. Detailed statistics are given in Table II (Luty, 2019).When the statistics are examined, EU citizens live in different types of houses. In addition, the second most preferred holiday destination by EU citizens is holiday homes. According to the statistics published by Statista, the holiday home sector's income for 2019 is 57,669 million dollars and the targeted amount for 2023 is 74,005 million dollars (Statista, 2019). It serves different booking portals in such a large sector. Large booking portals are trying to increase their customer portfolio and earnings with various artificial intelligence techniques. For example, providing appropriate opportunities to customers, regression analysis, the development of artificial intelligence tools to assist the host, and so on mentioned.

In this study, room classification process used in large reservation portals is discussed. The rooms in the holiday homes are classified to help the landlords and to provide accurate data to customers as much as possible. Artificial intelligence methods are still popular today. When the literature review was examined, Gürkaynak (2018) made ship classification using ResNet, Alex Net and VGGNet in his thesis (Gürkaynak, 2018). Seyfioğlu (2017) used Google Net, ResNet and VGGNet deep learning models to classify RF signals in the project he developed (Seyfioğlu, 2017). Toprak (2018) used AlexNet and VGGNet models on Railway Pedestrian Dataset (RAWPED) for the detection of pedestrians crossing the railway (Toprak, 2018). Örs (2018) studied SVM with AlexNet model in order to classify different wheat types (Örs, 2018). Kılınç (2018) achieved a success rate of 85 %90% with the model developed by AlexNet to detect individuals with Downsendrome (Kılınç, 2018). Zhou *et al*. (2017) developed an application using AlexNet to determine whether vehicle drivers were wearing seat belts (Zhou, 2017). In addition, with the ImageNet Large Scale Visual Recognition Challenge (ILSVRC), a more successful deep learning model has come to the fore each year. With this competition, AlexNet (Krizhevsky, 2012), ZFNet (Zeiler, 2014), VGGNet (Simonyan, 2014), GoogleNet (Szegedy, 2015), ResNet (He, 2016), ResNeXt (Xie, 2017) and so on. Many deep learning models have gained popularity.

In this study, the classification of the rooms in holiday houses is emphasized with ResNetder's learning model. In the study carried out with the dual classification process, the image of a holiday room was classified as “bedroom” or “bathroom”. The test and validation sets consist of public images obtained from Flickr. The procedures, materials and methods used and the results obtained in the following sections are explained in detail.

MATERIALS AND METHODS

The deep learning model used in this study was run with Tensor Flow using Keras. Keras is a high-level artificial neural network library. With the Python programming language, it enables the development of artificial neural networks on TensorFlow, Theano and Microsoft Cognitive Toolkit (CNTK). Central Processing Unit (CPU) or Graphical Processing Unit (GPU) support. It is preferred for the rapid execution of experimental studies (Keras, 2019). This study was conducted on GPU with Keras library. A high-end computer with Nvidia graphics card was used. Detailed technical specifications of the computer are given in Table III.
A data set specific to a German-based reservation portal operating in Europe was used in this study. This data set is not explicitly shared in any medium and its distribution is not permitted by the company. Most of the content in the data set consists of room images of holiday homes in the northern part of Germany. In the data set, there are 2 different categories as “Bedroom” and “Bathroom”. The images in the data set representing two different categories are given in Fig. 1.In this data set, which consists of a total of 30,000 images, each category has 15,000 images. For the 10,000 visual training stages in the categories, the remaining images were used for the testing and validation stages. The images used for testing and validation were obtained through Flickr. The distribution of the images in the data set is given in Table IV. ILSVRC has achieved different successes and deep learning models have been used frequently in the literature. In this study, the 50-tier configuration of the ResNet deep learning model winning the ILSVRC 2015 competition is used. The ResNet (Residual Network) is a deep-learning network structure with 18, 34, 50, 101 and 152 tier configurations. It has been proposed as a solution to disappearance and explosion problems as the networks deepen. It uses convolution filters of different sizes, including 1 x 1 convolution filters. Batch Normalization (BN) is used as normalization. Comparison of single model error results from Image Net validation set is given in Table V (He, 2016). The transfer process in ResNet model is shared in Fig. 2.

Applications: The ResNet model used in this study consists of 50 layers. The ResNet50 model was realized with the help of Keras. The input - output values and filter dimensions of the model have not been altered in any way and the original values of the model have been adhered to. The image of the ResNet50 model is shared in Fig. 3.The data set detailed in the previous section is made available for the ResNet50 model under different folders as test, validation and training. The data set was run on a total of 20 Epochs on the ResNet50 model.

At the end of 20 Epoch, 99.55% success rate and 1.37% error rate were obtained. The success and error rates obtained during the study are given in Fig. 4. Changes between Epoch steps are shared in Table VI.In order to examine the success and error rates obtained at the end of the training, the room visuals were given to the model in various variations. For the bedroom, different combinations of images with single beds, double beds, single cabinets or multiple cabinets, bunk beds and normal type beds were selected. For the bathroom, jacuzzi, shower, bathtub, closet, sink, mirror and so on. images are used in different combinations of elements. The visuals and classification rates used by the model are given in Table VII.

RESULTS

Accommodation, which is one of the most basic needs of people from the past to the present, can be realized in different ways under the influence of climate, topography, socio-cultural and socioeconomic conditions (Bozkurt, 2013). Today, we live in the house, the type of house, structure, number of rooms and so on. Depending on the circumstance’s kitchen, bathroom, bedroom, living room, garden, garage, winter garden, etc. there are various rooms and spaces (Özgür, 2010).When the holiday preferences of EU citizens are examined, it is seen that Holiday Houses is the second most preferred option for 2019 (Luty, 2019). Holiday houses can be of different combinations and types as normal houses. Depending on the visitor's budget, the location and the region they want to go, there are detached, semi-detached, flats, pools, parking lots or different types of holiday homes. The holiday home sector's income in 2019 is 57,669 million dollars (Statista, 2019). There are different booking platforms in this sector. Large booking platforms use a variety of artificial intelligence methods to assist customers and landlords. For example, a variety of in-depth learning practices for classifying rooms in holiday homes can be developed to help both guests and hosts. In this study, an application was developed for the classification of rooms in holiday houses by using ResNet network. With the double classification method, it was ensured to classify the bathrooms and bedrooms in holiday homes. The training dataset is specific to a reservation platform based in Germany and its distribution is not permitted by the institution.

Table 1. Distribution of population in EU and Euro area by type of household (4)

Country	Home Type (%)	Year		
		2018	2017	2016
Germany	Flat	56,3	56,7	57,1
	Detached House	26,4	26,4	26,1
	Semi-Detached House	15,8	15,7	15,5
Spain	Flat	64,9	66,1	66,1
	Detached House	12,9	12,3	12
	Semi-Detached House	22	21,4	21,5
France	Flat	-	33,1	31,5
	Detached House	-	43,5	44,6
	Semi-Detached House	-	23,3	23,7
Netherlands	Flat	20,1	18,9	18,8
	Detached House	17,5	17	17,8
	Semi-Detached House	57,9	58,7	58,4
United Kingdom	Flat	-	14,7	14,3
	Detached House	-	24,5	24,7
	Semi-Detached House	-	60,4	60,1

Table 2. Holiday preferences of EU citizens in 2019 (6)

Holiday Preference	Preference Percentage (%)
Hotels	48
Holiday Homes	34
Camping	11
Boat Traveling	6

Table 3. Technical characteristics of the computer on which the study was performed

Feature	Description
GPU	Nvidia GTX 2080Ti
RAM	32 GB
CPU	Ryzen Thread Ripper 2950X

Figure 1. Representative images in the dataset (Left: Bedroom, Right: Bathroom)

Table 4. Distribution of images in the data set

Label	Training Data	Test Data	Validation Data
Bathroom	10.000	2.500	2.500
Bedroom	10.000	2.500	2.500
Total	20.000	5.000	5.000

Table 5. Single model error results comparison from Image Net validation set (18)

Model	Error Top-1	Error Top-5
VGG Net	-	%8,43
Goog Le Net	-	%7,89
ResNet50	%20,74	%5,25
ResNet101	%19,87	%4,60
ResNet152	%19,38	%4,49

Table 6. Exchange of success and error rates between Epoch steps

Epoch	Success Rate (%)	Error Rate (%)
1	91,31	29,85
5	98,62	4,86
10	99,26	2,35
15	99,45	1,75
20	99,55	1,37

Table 7. Classification results of different types of bathroom and bedroom images

Image & Description	Classification Result	Classification Status
 Bedroom with two single beds	Bedroom	Successful
 Bedroom with double bed	Bedroom	Successful
 Bedroom with bunk bed	Bedroom	Successful
 Bathroom with bathtub and sink	Bathroom	Successful
 Bathroom with shower and toilet	Bathroom	Successful
 Bathroom with jacuzzi	Bathroom	Successful

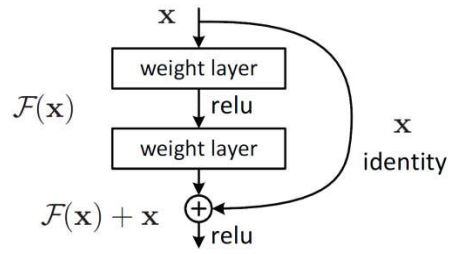

Figure 2. Transfer operation in ResNet model

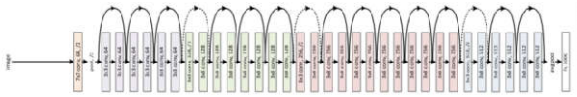

Figure 3. ResNet50 model

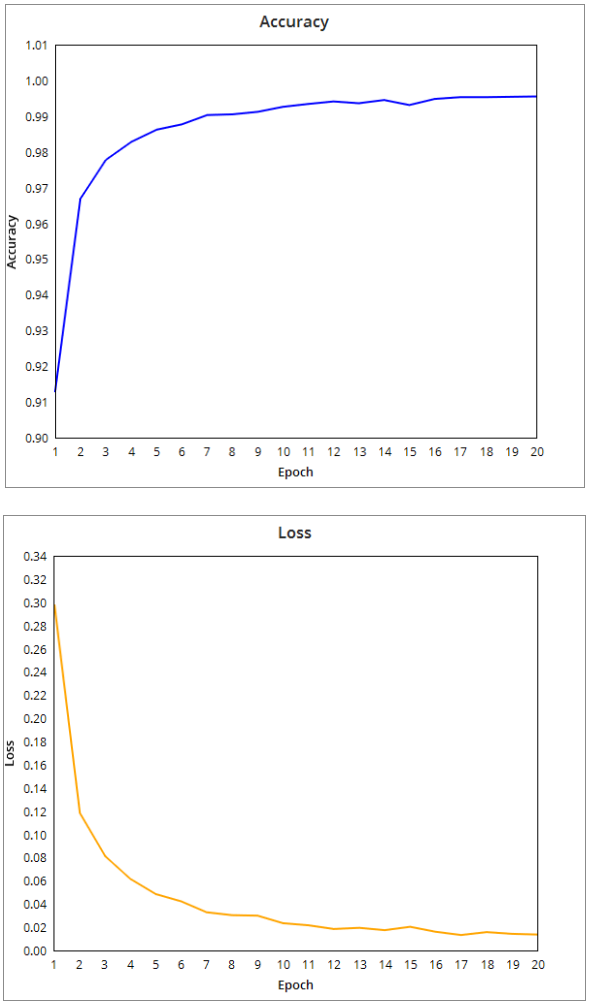

Figure 4. Variation of success (blue) and error (orange) rates during runtime

Test and validation datasets were obtained from Flickr. The data set contains 30,000 data, 20,000 training data, 5,000 tests and 5,000 validations. 15,000 of these data are bedroom visuals and the other 15,000 are bathroom visuals. The ResNet50 model is used with the Keras library. 20,000 training data and a total of 20 Epochs were run and training was carried out. At the end of the training, 99.55% success rate and 1.37% error rate were obtained. In the tests performed with bedroom and bathroom visuals with different configurations, the model has successfully classified all images. With this study, how ResNet model yields results with a previously untested data set, success and error situations are examined. Success and error rates can be improved by experimenting with different original data sets or by making modifications to the ResNet model.

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